PROJECT RISK PROPAGATION MODELING OF ENGINEERING, PROCUREMENT AND CONSTRUCTION

by

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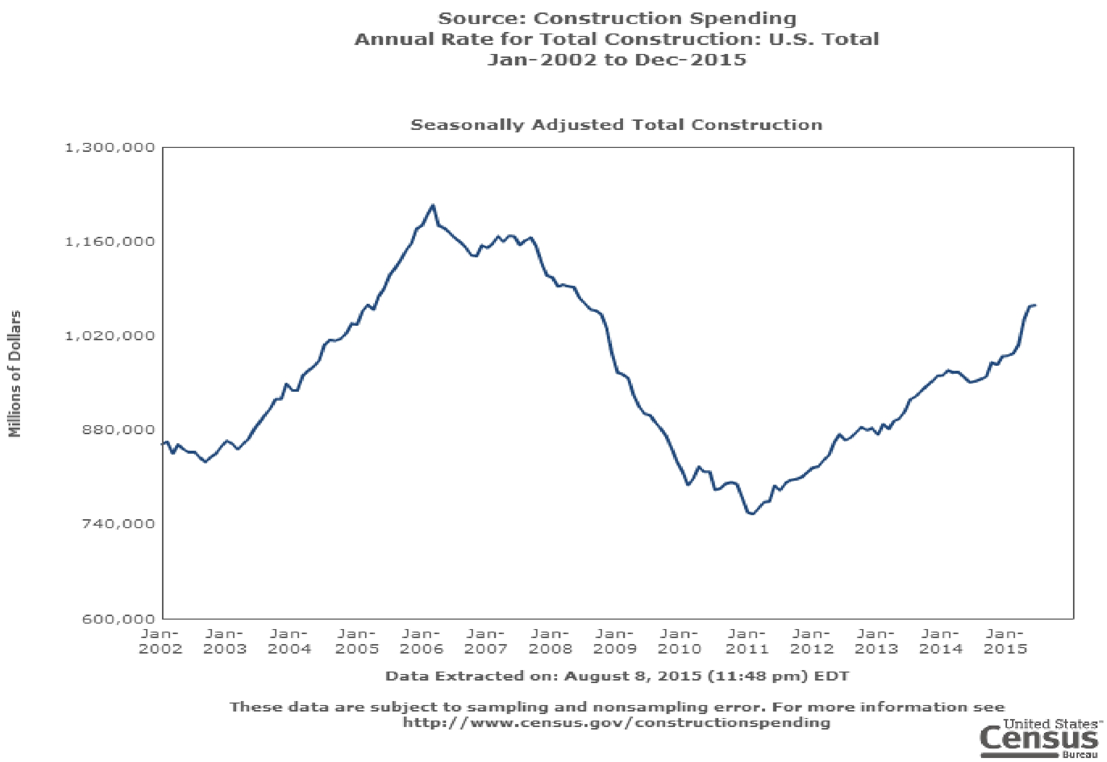
CHAPTER 1 - INTRODUCTION

1.1. Construction Industry

The construction sector has recently experienced significant expansion worldwide due growing demand from population increases around the world, as well as urbanization and the availability of new technologies. According to a report by United States Census Bureau (Figure 1), investment in construction increased by about 306 billion dollars from January 2011 to June 2015 and now amounts to 12 trillion dollars annually in the U.S. This represents a significant growth in this industry, and the figure indicates that this trend is expected to continue in the future.

Figure 1 - Investment In Construction Industry In The U.S.



Price Waterhouse Coopers International Limited (PWCIL) (2015) predicted that the volume of global construction output will grow by more than 70% to $15 trillion worldwide by 2025. The U.S., China, and India will account for almost 60% of all global growth. World construction markets are expected to increase from 52% to 63% by 2025, with China and India contributing most to growth in emerging markets.

Therefore, the construction industry must find innovative solutions and products for better city contribution since there will be two billion additional city dwellers, and sustainable urbanization will be a major construction challenge for human by 2050, forecasted by PWCIL (2015).

1.2. Construction Project Types

Our proposed work will focus on construction projects which can be divided into two major categories: residential (housing) 36% and nonresidential 64% in the U.S. Also, we can classify the nonresidential sector into commercial (28%), transportation (13%), infrastructure (6%), and industrial sector (17%) in the U.S. About 72% of construction activities are handled by private owners and 28% by the public (government) sector, according to the United States Census Bureau (2015).

Residential: Residential construction is often common of as the sector within the construction industry which has the most in common with manufacturing. Despite the towering skyscrapers in megacities, the most common method of residential construction is wood-framed construction in North America. Residential construction is the process of adding or modifying the structure to real property or construction of buildings.

Industrial: The information published by the U.S. Census Bureau (2015) indicates that construction investment in the industrial sector is about 17% of total construction investment and it increased by about 10 billion dollars from January 2002 to June 2015, currently amounting to 160 billion dollars annually in the U.S. This represents significant growth in this industry, and the figure indicate that this trend is expected to continue in the future. The construction projects related industries are quite diverse, and they include designing and building power generation facilities, oil wells (off-shore and land drilling), oil and gas extraction from shale, and so on. The industrial construction sector is one of most risky areas in the construction field, so one should be more careful about risk management and risk propagation in this area.

The project work for industrial facilities includes all construction and installation activities for new enterprises to put the plants in operation, as well as providing for the expansion and modernization of the existing plants. In the typical industrial facility construction project, the industrial company or a consortium of companies conceive and finance the project, and then engineering/architectural firms which team up with construction / installation contractors to deliver the project. Additional entities participating in the project include material and equipment suppliers, legal firms, government regulatory agencies, financiers and insures, and consultants. The industrial project work impacts all of these stakeholders, and often the public as well. The size of the projects, the complexities associated with their design, the duration it takes to complete them, contracting corruptions, and environmental and pollution problems make these projects highly expensive and challenging.

Commercial: Commercial building types can include office, health care, educational, lodging, amusement, and religious buildings as well as warehouses, and shopping malls. Designing commercial buildings, providing materials and service, executing them are so very risky, so members of project management teams should be careful about risk propagation from one phase to another phase.

Transportation: Highway and street expansions, tunnels and railroad projects are under transportation civil construction industry. Obviously, safety management is the area in the transportation field that carries the most risk. Also, a variety of climates and circumstances can affect those project objectives.

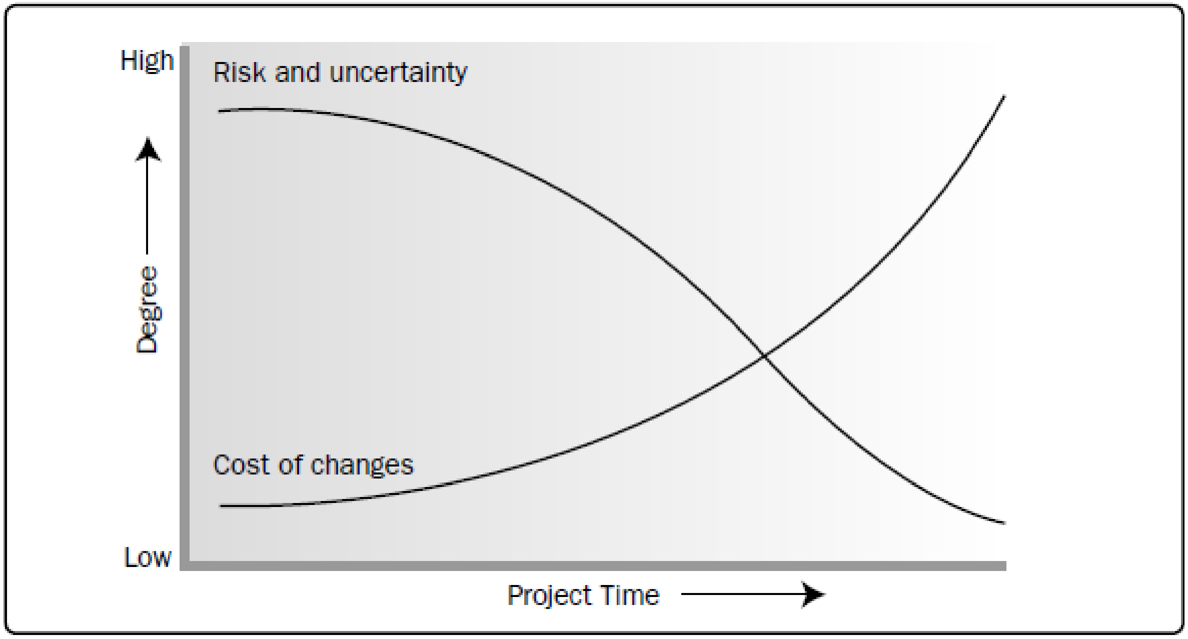
Infrastructure: Implementation water supply, sewage, disposal, and communication systems are parts of civil infrastructure projects. These disciplines are 6% of capital investment in construction segment in the U.S., according to the U.S. Census Bureau (2015). Differing site conditions, construction pollution, and environmental degradation may greatly affect project goals.

1.3. Construction Project Life Cycle

A project life cycle is a series of sequential phases that a project passes through from its initiation to its closure and what one must be done to complete the project work as was described by PMI (2013).

According to Figure 2, PMI (2013) claims that uncertainty is greatest at the beginning of every project and risk decreases over the life of a project. On the other hand, the cost of change is lowest at the start of the project and increases as the project progresses toward completion. For those reasons, in this investigation, we are going to identify the risk events in the initial phase and how to control risk propagation to other phases of a construction project.

Figure 2 - Risk and Cost (PMI, 2013)



The first level of Work Breakdown Structure (WBS) and Risk Breakdown Structure (RBS) should be the project life cycle and the high-level phase of the construction project is a portion of project life cycle. Thus, Engineering (E), Procurement (P), and Construction (C) are three components of a construction project life cycle.

1.4. Construction Project Phases (E, P and C)

A construction project can be logically divided into any number of phases. A phase of a construction project is a collection of tasks to complete the construction of one or more deliverables. Phases of a construction project are completed sequentially, but they can overlap.

It is generally recognized that engineering, procurement and construction (E, P and C) are three interrelated phases of a construction project. They are commonly incorporated in the contracts used to undertake construction work as EPC (or Turn-key) contract by general contractors. These phases can be defined as follow:

Engineering (E): Engineering (E) functions may include initiation, designing, planning and programming, estimating, and valuation as well as technical information and drawings control and recording. The engineering and design phase are closely followed by the procurement (P) phase. Engineering (E) is the process by which the needs, wishes, and desires of an owner or developer are defined, quantified and qualified into clear requirements. The work is highly multidisciplinary and highly technical in nature because of the constantly changing and improving technologies involved in design and construction.

Procurement (P): The Procurement functions may include procurement planning, conduct contracts, contract administration, and contract closing. It would be better to say that procurement is the acquisition of material from an external source to meet the needs of the project in terms of quality and quantity. It is generally accepted that purchasing; expediting, receiving, invoicing, and reconciliation are important activities in the procurement phase. This phase is also complex and dynamic due to communicating and integrating human resource and technology factors.

Construction (C): Directing, managing, performing and accomplishing the project work include providing the deliverables and managing work performance information. Construction (C) functions may include construction scheduling, on-site material handling, day-to-day management of construction activities, on-site communications, valuation and cash flow, and close out. Here, cost, schedule, quality, productivity, and safety must be simultaneously achieved, which presents managerial challenges. All of these factors lead to project risks that need to be correctly identified, evaluated and controlled.

In a typical EPC contract, a contractor is obliged to deliver a complete facility to the owner who needs only to "turn a key" to start operating the facility. Hence, EPC contracts are sometimes called turnkey construction contracts. However, when the scope is restricted to engineering and procurement, the project becomes an EP, E and P or E+P contract. This is often done in situations where the construction risk is too great for the contractor or when the owner self-performs the construction.

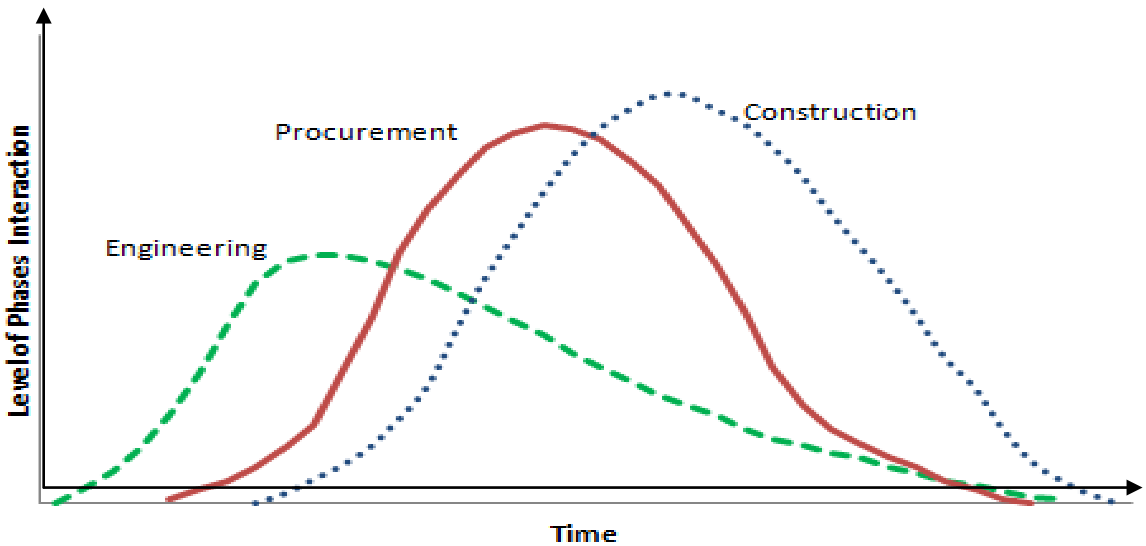
A contractor begins to construct its specified engineering facilities in construction (C) phase according to work packages prepared during the engineering phase and using equipment and materials obtained in the procurement phase. The sequencing of construction should be initially planned to reflect the most logical and cost-effective approach to meet startup and handover dates.

1.5. Process Group and Phases

A Process Group includes the constituent project management processes that are linked to the respective inputs and outputs, that is, the result or outcome of one process becomes the input to another. All construction Project Management Process Groups are linked by the objectives they produce. The Process Groups are one-time events; they are overlapping activities that occur at varying levels of intensity throughout the project.

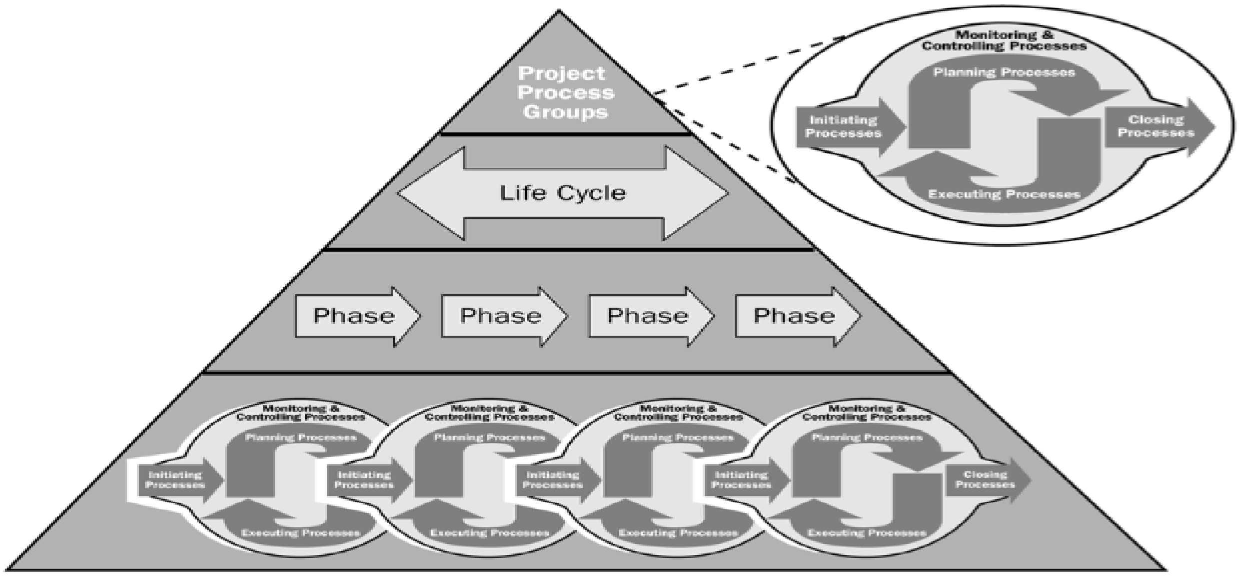
The Process Groups are not project phases. Where large or complex construction projects may be separated into distinct phases or sub-projects such as project engineering (E), procurement (P) and construction (C) all of the Process Group processes would normally be repeated for each phase or subproject. Figure 3 illustrates the Phases of a construction project and the level of overlap at varying times within a project.

Figure 3 - E, P and C Phases



PMI (2004) described that "when a project is divided into phases, the process groups are normally repeated within each phase throughout the project's life to effectively drive the project to completion. The process groups and their relationships are illustrated in Figure 4".

Figure 4 - Process Group – PMI (2004)

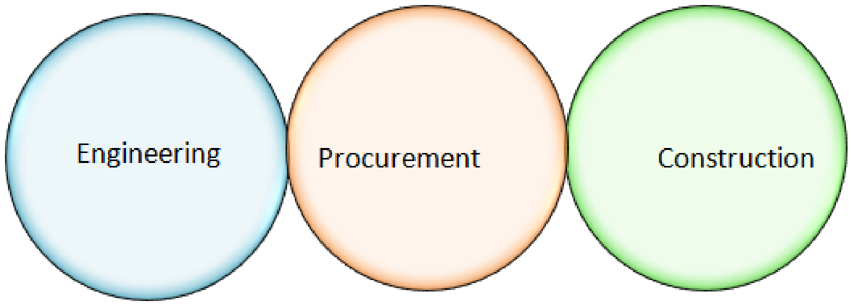


1.6. Construction Delivery Method and E, P and C

It is generally accepted that there are two type of construction project delivery method: Design-Bid-Build (DBB) and Design-Build (DB).

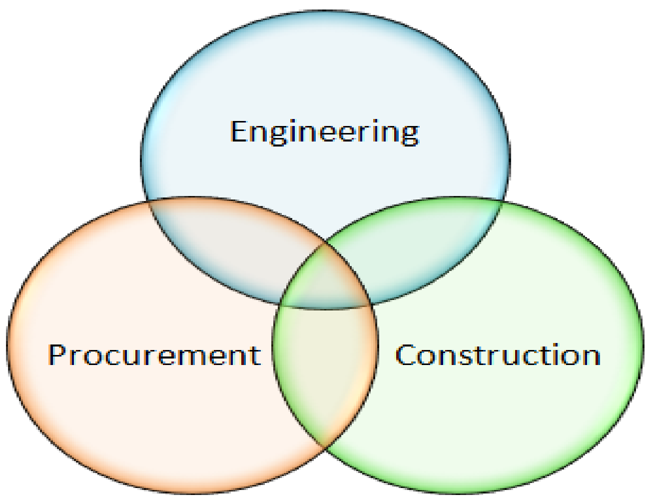
Design-Bid-Build (DBB) or Design-Award-Build (DAB) is a traditional construction delivery method in which the phases (E, P and C) of the construction projects are sequential. On the other hand, Design-Build (DB) is a modern delivery method where (E, P and C) phases overlap with each other. In fact, in the Design-Bid-Build (DBB) method, the Engineering (E) phase must be completed and all drawings should be generated then the Procurement (P) and then Construction (C) phases can be started. In Design-Build (DB), the material purchasing in the Procurement (P) phase can be started based on some drawings already designed, and the Construction (C) phase can be begun before those Procurement (P) and Engineering (E) phases are finished (Figures 5 and 6).

Figure 5 –DBB Method



Design–Bid-Build (DBB) Method

Figure 6 - DB Method



Design–Build (DB) Method

Although it is true that Design-Build (DB) is riskier than Design-Bid-Build (DBB), the delivery methods don't greatly affect the propagation of risks among the engineering, procurement, and construction phases of construction projects and the results of our investigation.

1.7. Construction Risks

There are many ways to define the term 'risk', but we will only focus on the most popular ones. The International Organization for Standardization (ISO 31000 (2009)) indicated that risk is the "effect of uncertainty on objectives". Project Management institute (PMI, 2013) says that risk is "an uncertain event or condition that if it occurs, has a positive or negative effect on one or more project objectives".

From a financial point of view, we can classify risks into two main categories: business risks and pure risks. Mulcahy (2009) described that pure risks have a negative impact (loss) but, business risks can affect a subject negatively and positively (loss or gain).

There is no doubt that there are a lot of risks in construction projects and in this study, the forty typical risk events in construction projects were identified from previous strong investigations that we will explain more in chapter two.

1.8. Uncertainty Model

Since ancient times, people have used models as a means of coping with the variability and complexity of their environment. We shall call such meshes or networks of cause-effect relationships causal models.

In this study, we decided to utilize a statistical model, namely, logistic regression. Although many models can be used to show risk propagation, such as artificial neural networks, structural equation models, and risk structural matrix, the logistic regression model is able to represent and help learn direct causal relationships. Also, we are interested in deriving cause-effect relationships from data to demonstrate and apply our ideas, as well as to evaluate the resulting algorithms. Further, we need to use probability theory as our foundation for risk propagation, which is an old and frequently tried theory that has withstood the test of time and has become one of the cornerstones of the risk sciences.

1.9. Advantage of the Risk Propagation Model

The developed risk propagation model offers a comprehensive look at the risk patterns that may emerge throughout the project because it contains (1) risk sources, (3) potential risk events/problems, and (3) the effects of problems in other phases (target) of the project's performance.

Uncertainty is the greatest and the cost of change is the lowest at the beginning of every project. Thus, controlling risk propagation into later phases reduces uncertainty and the cost of every construction project. The risk propagation model can be used to answer what-if questions at the early stages of the project and various managerial strategies can be developed to improve the system's vulnerabilities.

Risk propagation model, such as the predictive model, can be a risk identification tool for development of risk strategies at construction firms and projects. This model can act as a decision-support tool at the early stages, facilitating the assessment of the advantages and disadvantages of candidate projects.

1.10. Risk Propagation and Project Management Areas

There is no doubt that the main objectives of project management teams and project managers are risk management and risk propagation control. From the initial phase of a construction project, the project management team should identify high-level risks. Next, they should create a risk management plan and identify detailed risks, after evaluating them. They should define a response plan for critical ones in the planning phase. Consequently, they should control risk propagation based on the risk management plan during the project life cycle.

PMI (2013) believes that risk management is one area of ten areas of project management and that it includes scope management, time management, cost management, quality management, human resource management, communication management, risk management, procurement management, stakeholder management, and integration management. However, it would be better to say that risk management is project management because many project managers just do risk management and try to control risk and their propagation impacts during the project life cycle and engineering, procurement, and construction phases in construction projects.

In this research, we are more focused on project management areas which are believed to be more and risky. Descriptions follow:

Scope management: In the scope management process, the first step is defining the scope. We need to create a project scope statement as outlined in PMI (2013). Project scope statement may include the product scope, deliverables, product acceptance criteria, constraints, and assumptions analysis. Assumption analysis is part of the risk management process and determines what is in the project and what is not in the project or what may have an impact on the project. Therefore, we should identify high-level project risks and register them in that document. Then, those risks and assumptions should be monitored and updated by the project team during the life cycle of the project.

On the whole, changing any critical factor of the engineering, procurement, and construction phase may propagate to the scope of another phase. Thus, a project management team should have a plan for risk propagation management.

Time management: Time is money; as a result, time and cost management can be the riskiest areas of project management. The time management process includes defining activities, sequencing activities, estimating activity resources, estimating activity duration, and developing a schedule during the planning phase. To achieve all these tasks we need the risk register of the project which is one of the outputs of the risk management process. Some estimation methods such as the "three point technique" are based on standard deviation and estimates ranges which are used to assess risks PMI (2013). During the construction period, the initial risk register should be updated and hidden risks should be revealed via progress elaboration. Fast tracking and crashing are two methods of schedule compression which increase risk propagation to other phases of construction projects. Iteration in the time management process happens based on updating the risk register and its affect on risk propagation.

Cost Management: Creating a "Plan Cost Management", estimating cost, and determining budget are tasks of the cost management process during the planning phase. It is generally accepted that those mentioned tasks have a strong relationship with risk identification and propagation. There is no doubt that if we couldn't identify and control from initial phases, they will be propagated to other phase and extend the time and cost of the project dramatically. Controlling and monitoring the cost of construction projects is very closely related to risk propagation control.

Quality management: The quality management process includes providing a quality plan and performing quality assurance and control in construction projects. The project team should focus on hazards and contingency quality problem during engineering, procurement, and construction phases. If not, a quality risk can propagate from one phase to another easily and increase the cost of quality which includes the costs of conformance (training, studies, and survey) and nonconformance (rework, scrap, inventory costs, warranty cost, and lost business).

Resource management: After planning for resource management in the engineering phase, the project resources should be acquired and the contracts should be administered in the procurement phase. Additionally, the project team should be developed and managed in the construction phase. All of those activities have a strong relationship with risk propagation and risk management. For example, reducing human resources or using unskilled designers in the engineering phase may propagate a delay or rework risks to the construction and procurement phase.

Communication management: The communication and stakeholder management, like all project management areas, needs a plan that should be generated in the engineering phase. At the same time, related risks should be identified and must be considered in the plan. Next, stakeholders and communication should be controlled by the project team during the construction phase of the project. Thus, the risks in the construction phase and the risks propagated from the engineering and procurement phases are impacted by communication and stakeholder management. Inadequate communication management can interrupt project information and the flow documents among the construction, procurement and engineering phases.

Safety management: Safety hazards usually surface in the construction phase, but they can be identified and evaluated in the engineering phase. Additionally, the appropriate response should be predicted in the engineering phase. However, those tasks can be repeated and upgraded during the construction phase of the construction projects.

In the final analysis, there is a strong correlation among risk propagation management and project management areas. For that reason, we created Survey Two to understand the relationship among the engineering, procurement and construction (EPC) phases and project management areas (PMA). As a result of Survey Two, we developed a model by using a logistic regression model. Thus, we could interpret the model and understand which risk events have the greatest impact on project management areas and which project management areas are the most affected by risk events of in the engineering, procurement and construction phases. We will discuss these in more detail in Chapters Three and Four of this dissertation.

1.11. Study Scope

Our research study scope will be limited to examining risk propagation factors encountered in construction projects. In this context, the construction project is defined as a one that operates and delivers services for industrial, residential, commercial, transportation, and infrastructure work. These include national and international construction projects around the world.

In this study, we considered effects of risk events on an entire construction project, not only one portion of it. It would be better to say that we investigated the risk events of construction projects from the owner's view (top to bottom), but not from the perspective of other stakeholders such as subcontractors who are involved in some parts of construction projects.

Risk event in construction projects can be viewed from two perspectives. First, a single risk occurs and it impacts another individually. The second belief is summing the propagation impacts when the risk has occurred. Our measures are based on the second scenario analysis. Also, a risk event can propagate inside the source phase or to other target phases. In this research, we focused on risk event propagation from one phase (source) to another phase (target).

1.12. Problem Statement

The construction industry is more complicated than other types of industry, because it involves high quality standards, complicated technology, a variety of stakeholders, challenging environmental issues, huge investments, complexities in the supply chain, sophisticated and powerful equipment, the need for expert workers and specialized training, maintenance issues and warranties, economic and political factors, and other similar features which may cause an uncertain and unpredictable environment for construction projects. Changes in any of the aforementioned variables can be a threat, as well as an opportunity, for the entire project.

Risk can be defined as the effect of uncertainty on project objectives and outcomes while these may be positive or negative. Thus, risk propagation management approaches must align with increasing the probability and impact of positive events and decreasing the probability and impact of negative events on a given project. Risk propagation management challenges may be encountered in program planning, risk identification, classification, evaluation, response planning and implementation, and monitoring and control.

A typical approach includes the systematic application of management policies, procedures, and practices for the tasks of communication, consultation, establishing the context, identifying, analyzing, evaluating, treating, monitoring and reviewing risks. Factors affecting risk may be related to financial aspects, quality standards, social impact, environmental constraints, safety considerations, communication challenges, contractual matters, design and technological issues, resources and stakeholder inputs, and project schedules.

Risk propagation management is one of the most critical fields that should be controlled in every phase of a project. Risk event can transfer from one phase to another phase very quickly and can cause more damage in other phases. The previous researchers have conducted some investigation on risk propagation in the supply chain, but no one has studied risk propagation among engineering, procurement, and construction phases of a project. Therefore, in this research, we covered this gap and show which risk has the most impact on other phases and which phase is more vulnerability. Then, we try to understand how we can control the risk propagation among the engineering, procurement, and construction phases before it is too late. Reacting quickly and logically can help to reduce damage and the cost of the project. This happens when one can categorizes the risks, evaluate them, and understand risk interrelationships. We implement an action to avoid risks propagation and amplification to the rest of the project.

While there is a fair amount of information on risk propagation modeling for construction projects, there is a dearth of publications in the scientific and engineering literature on the construction projects in terms of risk propagation management. The focus of the proposed study will be on risk propagation. Therefore, there is a need to undertake a research project to identify the significant factors affecting risk propagation, and develop a model with the aim of understanding, quantifying and evaluating risks arising in construction projects.

The proposed research will determine those actions that trigger risks to gain an in-depth understanding of how and why they occur so that mitigation and control strategies can be developed. If proper precautions are taken, and the root causes of those risk events are understood, the result of the projects can be improved successfully. The information and knowledge derived from this research could then be used to develop more effective risk propagation management methods in the construction field.

1.13. Research Questions

Based on the above considerations, the following research questions were formulated for this study.

RQ1: What are the typical risk events in regards to their occurrence in different construction project phases (engineering, procurement and construction (E, P and C))?

RQ2: What is the probability of the risk events identified in theRQ1?

RQ3: How does each risk event identified in RQ1 have impacts on other construction phases (E, P and C)?

RQ4: How can the top risk propagation events identified in RQ3 and RQ2 be ranked based on their probability and impact on different construction project phases (engineering, procurement and construction (E, P and C))?

RQ5: What is the highest ranked risk propagation event based on the impact and probability study in an entire construction project?

RQ6: What is the highest ranked phase propagation based on the impact and probability study in a construction project?

RQ7: Based on the logistic regression model methodology what would be the best model to represent the risk propagation on the identified project knowledge base areas?

RQ8: What would be the recommendations in terms of risk propagations management based on the findings from this study to reduce the impact and the probability of top risk events in a project?

1.14. Research Objectives

Continuing on from these research questions, the following research objectives were formulated for this project:

- To identify the factors involved in risk propagation and management for construction projects;
- To understand the relationships among these risks with specific emphasis on factors categorized under engineering, procurement and construction phases (E, P and C);

- To establish a process for risk propagation management and analyzing the cross-impact on the construction phases of projects;
- To develop risk propagation models by using logistic regression model applicable to construction projects;
- To develop recommendations for improving construction risk management.

1.15. Research Approach

The research approach of this study incorporates two parts, presented as follows:

In the first part, a survey was designed to rate risk events for each phase of the construction project (E, P and C), as well as the entire project. In this section, we asked respondents to rate the identified risks' in terms of their probabilities as well as their impacts on other phases. This effort was divided into four stages as described below:

First, forty critical variables (risk events) were and their interrelationships were identified through a comprehensive literature review, coupled with a series of interviews with practitioners who were involved in the engineering, procurement, and construction in construction firms or were university researchers. For example, we utilized the results published by the Smart Marker Report (2014) which described that perspectives vary among owners, architects, and contractors on the relative importance of key drivers of uncertainty on construction projects.

Second, the risk events were classified into three main categories as Engineering, Procurement, and Construction by the construction experts (See Table 1, Table 2, and Table 3 in Chapter 3).

Next, a comprehensive survey (Survey One) was developed to evaluate each risk events from a construction phase in terms of impact on other phases (See Appendix A).

Last, we measured the scores of every risk event and we ranked them. Then, based on the Pareto principle, we separated the top eight of them for the next section.

In the second section, we are going to determine the interrelationships among risk events of E, P and C phases associated with project management areas. To achieve that purpose, we followed the following three steps:

First, the identified risk events (independent variables) were classified under E, P and C (See Table 1, Table 2, and Table 3 in chapter 3).

Second, we created a new survey (see Survey Two in Appendix B) to measure the impact of the risk events (independent variables) on project management areas (dependent variables).

Third, based on logistic regression model methodology twenty-eight risk propagation models (RPM) were created to understand and analyze risk propagation behavior in construction projects and find some way to control that. In other words, we made twenty-eight models to represent the impact of risk events on the identified project knowledge base areas. In these models, dependent variables are defined as whether they have a meaningful impact on seven project management areas (scope, time, cost, quality, resource, safety and communication).

CHAPTER 2 - STATE - OF - THE - ART REVIEW

The chapter surveys the literature to date on the risk propagation modeling in the field of engineering, construction and procurement. Thus, this chapter provides a broad review of all aspects of risk management in construction projects. Special attention is directed to how risk related data has been organized and analyzed by other researchers. This state-of-the-art (SOA) review helps researchers recognize the risks for personnel and applicable remedies for these risks.

This comprehensive search includes a review of the books, standards, published papers, articles, and theses pertaining to "risk events in construction projects" as part of the proposed research effort. More specially, searches were conducted of all relevant construction journals such as the Journal of Construction Engineering and Management, the Journal of Safety Research and other published reports and documents from recognized sources. All identified papers and reports reviewed to expand our knowledge and understanding of the factors about the cause and prevention of propagation risks in the construction industry.

2.1. Risk Management in Construction Projects

Abdelgawad and Fayek (2010) examined the concept of risk management in the construction industry by combining fuzzy Failure Mode and Effect Analysis (FMEA) and fuzzy Analytical Hierarchy Process (AHP). The intent was to identify critical risk events in a timely manner so that corrective actions can be established effectively. The developed model was verified by implementing it in a pipeline project.

Taylor and co-authors (2011) conducted research on risk management in nuclear power plant construction. The study focused on social risk perception. A new dynamic simulation model for society, public policy, and NPP construction was established and used as an experimental platform to test two strategies for the next generation of nuclear plant construction projects, combining nuclear plant licensing and smaller nuclear reactors.

Shih and co-authors (2009) investigated the geographical areas where there are U.S. power plants and coal mines, with their rail transportation system, to gain insights into the needed risk management and emergency response. The goal of the research was to develop a power generation supply vulnerability assessment framework and a risk assessment framework. A model was implemented for estimating which power plants will be potentially impacted from external and internal risk events such as earthquake or supply chain disruptions.

Wambeke, Liu, and Hsiang (2012) studied the risk assessment matrix and used the Last Planner System (LPS) in mechanical related to construction tasks. They demonstrated how using the LPS method reduced and/or eliminated variation for the mechanical contractors involved while using a risk assessment matrix as a new and effective means of prioritizing causes of variation to be targeted first for reduction. It was emphasized that the methods used resulted in a 35% higher productivity and 13:1 benefit–cost ratio as compared to traditional projects.

Tang et al (2007) surveyed project risks, the application of risk management techniques, and the barriers to risk management in the Chinese construction industry. The study showed that the five most important project risks were “poor quality of work”, “premature failure of the facility,” “safety,” “inadequate or incorrect design,” and “financial risk.”

All of these studies show us that a construction project is one of the riskiest and complicated areas. As a result, the authors firmly believe that risk events should be identified and managed as soon as possible in construction projects. Thus, they also introduced a variety of tools and techniques (e.g. FMEA and LPS) for managing risks in construction projects which can be used for future investigations.

2.2. Risk Propagation

Chao and Franck (2011) suggested a risk modeling interaction in a simulation technique to analyze a propagation behavior in the risk network. The aim was to support decision-makers in planning risk response actions with a structured and repeatable approach. They simulated the risk propagation in the network to obtain different indicators for risk prioritization, such as criticality and the refined risk frequency. Also, a sensitivity analysis was performed to enhance the reliability of the network analysis phase. In this study, there are two types of mitigation action strategies included: a classical mitigation strategy against individual risks and a non-classical mitigation strategy, which mitigates risk propagation instead of risk occurrence.

Myles et al. (2014) introduced a framework to measure risk propagation in a supply network. In other words, they utilized a Bayesian Network (BN) approach and developed a model in terms of the risk propagation in a supply chain field. Since the underlying model allows for complex queries to be inserted, contingency plans and risk propagation management strategies may also be developed around the measures. They explained that a risk may propagate in one of two directions: either upstream or downstream as well as inbound to and outbound from a location in the Bayesian network (BN). In this research, uncertainty and risk were studied in a variety of different fields which model the propagation and structure of risk.

Giffen and co-authors (2009) also discussed some patterns defining local propagation motifs and defining relationships among two or three elements. They were more focused on global patterns, which are potentially the combinations of the local ones, like long propagation chains, heterogeneous propagation chains, and loops.

Feng et al. (2013) developed a security risk analysis model (SRAM) to identify the causal relationships among risk factors and analyze the complexity and uncertainty of vulnerability propagation. They described four classes of learning Bayesian Networks (BNs) from data: known structure and observable variables, known structure and unobservable variables, unknown structure and observable variables, and unknown structure and unobservable variables. Additionally, learning (BNs) consists of structure learning and parameter learning. There are two main approaches to structure learning: constraint-based and score-based. A structural BN learning algorithm requires the determination of two components: a scoring function for candidate network structures and a search algorithm that does the optimization.

There is no doubt that risk propagation from one phase (source) to another phase (target) can impact on the project objectives. The risk propagation management is more important than risk management individually; when a risk propagates from one stakeholder to another one, it can boost the risks since target stakeholder may not aware from that or may not ready to counteract against that risk. The aforementioned articles look for a way to introduce the risk propagation concept and show how we can control them.

2.3. The Engineering, Procurement and Construction Phases

There are a large number of published papers on construction risk management, but relatively few address risk propagation in construction projects by focusing on the engineering, procurement, and construction (E, P and C) phases. The majority of the papers from the construction industry primarily emphasize improving productivity, cost-benefit, and supply chain relations.

Jianhua and Yeo (2000) proposed the application of critical chain project management and supply chain management in the management of risk of EPC projects with a special focus on procurement. In this study, the characteristics and nature of EPC projects and maps of project processes were investigated. Then, a 'to-be' model was proposed by applying the concepts of supply chain management and critical chain project management based on the theory of constraints in EPC construction projects. Also, Zhao (2011) analyzed the EPC contract and the application of supply and critical chains based on the combination of purchasing theory and an EPC project procurement model which can heighten the efficiency of engineering procurement. He also believed that the adoption of supply chain and critical chain management to reduce the joint thinking in EPC project procurement and reduce the risk of uncertainty. Based on the result of the model, the author claimed that there are three major factors in an EPC project procurement model: culture, processes and information technology.

Yang and Wenhua (2014) offered a business model by combining building information modeling (BIM) and engineering-procurement-construction (EPC) contract method. They claimed that the new technologies such as cloud services and collaborative design will profoundly influence the traditional business model and reduce the impact of the risks of cost and schedule in construction projects.

Zhihong and Xiaoguang (2013) analyzed the engineering, procurement and construction phases from two perspectives: that of the owner and contractor. They also explained about some risk events in equipment and materials that are a high proportion of total investment, as well as the simultaneous design and procurement in construction projects. They said the interaction among the engineering, procurement and construction phases as coordination and matching can make effectively shorten the construction period.

Dividing a construction project into three phases of the engineering, procurement and construction phases can help us understand the risk propagation concept in that type of project. A construction project progresses during the life cycle of the project and moves from one phase to another. Consequently, the contractors of that project should also be changed simultaneously. Thus, how to manage risk propagation among those phases is critical. Zhihong and Xiaoguang (2013), Jianhua and Yeo (2000), Yang and Wenhua (2014), and Zhao (2011) understood the concept of that and they tried to look at E, P and C from different angles to analyze the relationships among them.

2.4. Source of Risk Events

Smart Market Report (2011) collected a list of the greatest construction risk events by surveying construction experts. Next, they sorted the risk events (independent variables) into several categories such as the construction phases, types of the construction project, internal and external categories. Finally, they analyzed the risk events, mitigation factors, and triggers. Also, this team published another report in 2014 which shows the top factors that cause uncertainty with the greatest impact on schedule, cost, and quality in construction projects. They also discussed opportunities (positive risk events) for performance improvement such as using building information modeling (BIM) in construction projects.

Yu and Wang (2011), proposed the Interpretive Structural Modeling (ISM) method which is the most effective solution for risk event analysis of EPC projects. They selected eleven main risk events identified (group brainstorming method) from the EPC contractors were assessed by the ISM method. Next, a Risk-Structure-Matrix was set up which shows the relationship among the risk events.

Mubin and Mannan (2013) proposed an evaluation model and a list of risk events for both owner and contractor in EPC projects in the oil and gas sector. From the contractor's perspective, they also proposed proper mitigation measures for all the critical risk events to complete a construction project successfully. Further, Baram (2005) provided a list of risk events in EPC construction projects and analyzed the Project Manager's Roles and Responsibilities in this regard.

In our investigation, the forty typical risk events in construction projects were identified from the aforementioned articles and interview with some risk practitioners. Smart Market Report (2011) and (2014), Yu Ning and Wang (2011), Mubin and Mannan (2013), and Baram (2005) introduced some critical risk events which can help us to concentrate on threats and opportunities of a construction project. Later, the risk events were decreased for the risk propagation modeling that we will discuss further in chapter three of this investigation.

2.5. Bayesian Networks (BN)

Bayesian networks (BN) consist of a set of statistical conditional independence statements that are implied by its structure. Only in the BN literature do we find claims of being able to represent direct causal relationships.

Dimitris (2003) determined the reasons for choosing Bayesian Networks as follows:

1. They are graphical models, capable of displaying relationships clearly and intuitively.

2. They are directional, thus being capable of representing cause-effect relationships.

3. They handle uncertainty through the established theory of probability.

5. They can be used to represent indirect in addition to direct causation.

Bayesian networks have been using for over three decades to model risk. Dimitris explained that “Typically, Bayesian networks consist of two primary components: the subjective causal relationships determined either by learning algorithms or expert opinion and the objective conditional probability distributions.”

Bayraktar and Hastak (2009) presented the functionality and application of a decision support system in a three major level framework for predicting the influence of decisions made by state highway agencies regarding important work zone project variables by using Bayesian Network modeling.

Durgaprasad and Rao (2012) indicated that decision makers and analysts can take into consideration information contained in fragmented expert knowledge and the many parameters involved in complex problems in building Bayesian Networks. They proposed the use of a graph theoretical technique for processing knowledge and building Bayesian networks in developing decision support systems. Also in another article, Durgaprasad et al. (2012) demonstrated new approach graph-theoretic techniques by setting up the flow of information for fragmented knowledge for building BNs. They explained that a fragment of knowledge is a set of events/parameters and their relationships which contribute to a decision analysis. These fragments of knowledge are represented graphically, and they may form a coherent body of domain experts’ fragmented knowledge when they are connected based on their common parameters/events.

Gupta and Kim (2007) proposed how to link BN (Bayesian Networks) and SEM (Structural Equation Model) by considering the process from identification of causal relationships to decision support, and they examined the integrated approach for customer retention in a virtual community.

Badreddine and Amor (2010) offered a new Bayesian approach to construct bow-tie diagrams for risk analysis. They suggested adding barrier implementation in order to construct the whole bow ties. Then, they used the numerical component, previously defined in the learning phase, and the analytic hierarchical process (AHP). The principle of the bow-tie technique is to build for each identified risk (also called top event (TE)) a bow tie representing its whole scenario on the basis of two parts: The first part corresponds to the left part of the scheme which represents a fault tree (FT) defining all possible causes leading to the (TE). The second part corresponds to the right part of the scheme which represents an event tree (ET) to reach all possible consequences of the TE.

Feng et al. (2013) developed a security risk analysis model (SRAM) in order to identify the causal relationships among risk factors and analyze the complexity and uncertainty of vulnerability propagation. They stated that there are four classes of learning BNs from data: known structure and observable variables, known structure and unobservable variables, unknown structure and observable variables, and unknown structure and unobservable variables. Additionally, learning BNs consists of structure learning and parameter learning. There are two main approaches to structure learning: constraint-based and score-based. A structural BN learning algorithm requires the determination of two components: a scoring function for candidate network structures and a search algorithm that does the optimization.

2.6. Structural Equations Model (SEM)

Eybpoosh et al. (2011) demonstrated that causal relationships exist among various risk factors that necessitate identification of risk paths by utilizing structural equation modeling (SEM) techniques, rather than individual risk factors, during risk assessment of construction projects. A risk-path model can answer what-if questions, and SEM is a predictive and decision support model. For developing a risk-path model, first, a list of risks should be provided as independent factors. Second, all possible multiple risk scenarios should be determined. Then, they should define the interrelationships among various risk factors and the proposed “risk paths” to decision makers.

Molenaar et al. (2000) presented the results of a structural equation model (SEM) for describing and quantifying the fundamental factors that affect contract disputes between owners and contractors in the construction industry. The set of structural equations provided insight into the interaction of the variables that was not apparent in the previous original logistic regression modeling methodology.

Wong and Cheung (2005) employed the structural equation modeling (SEM) technique to gain a better understanding of their partnering objectives and thus ensure partnering success. The findings of the study support the hypothesized positive relationship between the partners’ trust level and partnering success.

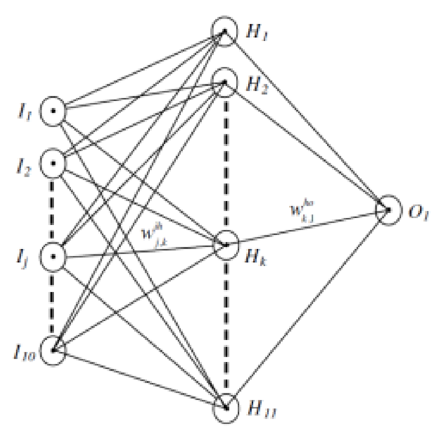
Chen et al. (2012) applied the structural equation model (SEM) to explore the interrelationships among the Critical Success Factors (CSFs) in construction projects. They developed SEM in the following steps: define the measurement and structural components to set up a hypothetical model, evaluate the verification of hypothetical model, assess the verification of the final model and interpret it. To establish the hypothetical model, three professionals in the construction management field were interviewed on the basis of their knowledge to make assumptions about the interrelationships among the subcategories of variables (CSFs).

2.7. Artificial Neural Network (ANN)

Patel and Jha (2014) developed an artificial neural network (ANN) model to predict the safe work behavior of employees. The model utilizes safety climate constructs (determinants) as inputs and safe work behavior as an output. Also, a three-layer feedforward backpropagation neural network was appropriate in building the model which was trained, validated, and tested with sufficient data sets.

The ANN was developed from neuroscience generalizations of mathematical models based on human neural biology. The ANN is composed of nodes connected by directed links. Each link has a numeric weight (Figure 7).

Figure 7 - Artificial Neural Network (ANN)



Artificial neural networks have many advantages over conventional methods of modeling due to their distinct features, and they are able to resolve complex nonlinear relationships with a greater degree of accuracy

Wang and Gibson (2010) and Rumelhart et al. (1994) explained that artificial neural network-based models generate a superior prediction in comparison to those obtained from regression models.

Gerek et al. (2014) compared the performance of the feedforward neural network (FFNN) with a radial basis neural network (RBNN) in modeling the productivity of masonry crews. They determined the relationships between productivity and influencing factors by using two ANN techniques (the feedforward neural network (FFNN), and the radial basis neural network (RBNN)) to better understand crew productivity in masonry work. Initial estimated weight values were progressively corrected during a training process (at each iteration) that compares predicted outputs with known outputs, and it back-propagates any errors to determine the appropriate weight adjustments, which is necessary to minimize the errors. RBNN (also called a localized receptive field network) is composed of two layers whose output nodes consist of a linear combination of the basic functions. Since the output layer implements a linear regression, the weights (parameters) of this regression are only adjusted. Demuth and Beale (2000) also said that the multilayer feed forward network with back propagation (BP) is efficient for performing any linear or multivariate arbitrary nonlinear computation and it can approximate any continuous function to meet the desired accuracy. However, the BP algorithm may cause an overfitting problem because it is slow for convergence, which is the eventual minimization of error between the desired and computed output.

Yunna and Zhaomin (2008) proposed a new evaluation model that combined the ant colony algorithm (ACA) with the radial basis function (RBF) neural network, which performed better in comprehensive mapping ability, evaluation accuracy, convergence rate, distributed computation of ACA and training span. A typical RBF NN input space can be normalized or an actual representation can be used. The linear coefficients of the output layer are adjustable.

2.8. Risk Structural Model (RSM)

Fang and Marle (2011) proposed a risk model interaction in simulation to analyze a propagation behavior in the risk network. The aim was to support decision-makers in planning risk response actions with a structured and repeatable approach. They simulated the risk propagation in the network to obtain different indicators for risk prioritization, such as criticality and the refined risk frequency.

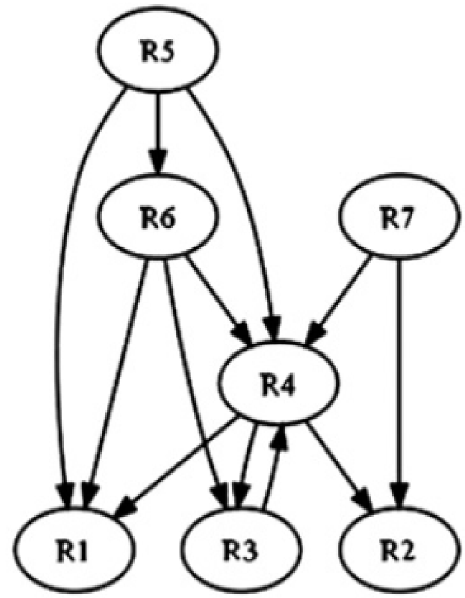
Eckret and co-authors (2004) designed the four following categories of risks: constants, absorbers, carriers and multipliers in the context of change propagation in design projects.

Giffin and other co-authors (2009) also suggested some patterns defining local propagation motifs and defining relationships among two or three elements. In fact, they were focusing on more global patterns, which are potentially the combinations of the local ones, like long propagation chains, heterogeneous propagation chains, and loops.

First, Steward (1981) introduced the design structure matrix (DSM) method as a practical tool for representing and analyzing relations and dependencies among the components of a system. Next, Fang and Marle (2011) utilized that idea to develop a cause–effect risk model called the Risk Structural Matrix (RSM) (See Figure 8).

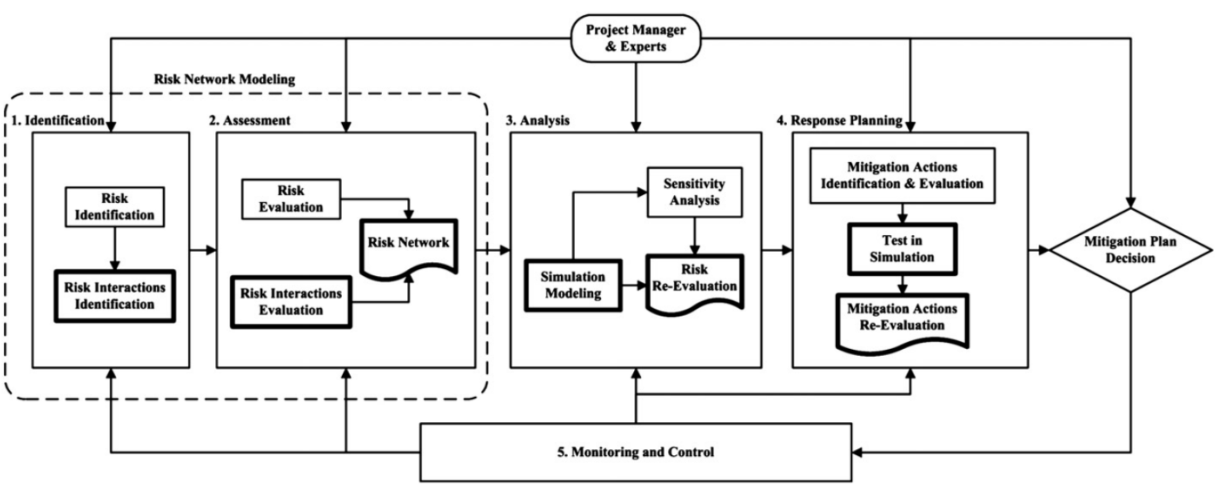
Figure 8 - Risk Structure Matrix (RSM) (Fang and Marle 2011)

	R1	R2	R3	R4	R5	R6	R7
R1				1	1	1	
R2				1			1
R3				1		1	
R4			1		1	1	1
R5							
R6					1		
R7							



Fang and Marle (2011) also suggested a framework for a decision support system (DSS) with five stages: (1) risk network identification; (2) risk network assessment; (3) risk network analysis; (4) risk response planning; and (5) risk monitoring and control (Figure 9).

Figure 9 - Decision Support System Based on RSM Fang and Marle (2011)



2.9. Risk Modeling by Using Logistic Regression

Kazan (2013) analyzed fatal and non-fatal accidents in terms of equipment operators and on-foot workers by utilizing logistic regression models, cross tabulation, and univariate analysis. In this study, the degree of injury indicating the severity of an accident outcome (fatal vs. nonfatal) was selected as the dependent variable, and a variety of factors potentially affecting the outcome comprised the independent variables. Also, cross tabulation results enabled the evaluation and understanding of associations among the research variables, while logistic regression yielded predictive models that assisted in explaining accident severity in terms of the contributing factors. He concluded by eliciting information from construction accident data that multivariate analysis serves as a much more powerful tool than univariate methods.

Cheung, Yiu, and Chan (2010) explored the potential for predicting project dispute resolution satisfaction by utilizing the logistic regression method. They described that the achievement of project dispute resolution satisfaction (DRS) is one of the factors critical to the success of a project. Thus, they investigated disputes in construction projects which are crucial risk events. For that reason, they compared two model; multivariate discriminate analysis (MDA) and logistic regression (LR). The findings suggested that the logistic regression (LR) technique provides a higher hit rate for this research and thus a higher proportion of correct classification. However, both models indicated that “design changes” are the root causes of adverse project DRS. Finally, they concluded that design change as a risk event is a critical cause of construction disputes and disruptive to project progress.

Fang et al. (2004) created a risk assessment model of tendering for Chinese building projects based on questionnaire investigation and the use of logistic regression. The findings showed that the six risk factors (source of project funds, the reasonableness of bid price, the existence of cooperation between contractors and owners, bidding competition intensity, owner type, and degree of support from the contracting company to its projects) can be used to assess the tendering risks of building projects. They claimed that the model can be helpful for contractors in making decisions for tendering of building projects in china and international construction projects.

Wong (2004) provided the logical scope of the contractor selection process in the United Kingdom by classifying contractor performance into good and poor groups. In this study, 31 clients' tender evaluation criteria were selected to establish a logistic regression model for predicting contractor performance. The proposed model was created based on 48 the United Kingdom private and public construction projects and it was validated in 20 independent cases. He used the logistic regression method to construct a "causal" function where the qualitative and quantitative independent variables by the combination of ordinal data and ratio variables.

Kazan (2013) on safety management, Cheung, Yiu, and Chan (2010) focusing on project success, and Fang et al. (2004), and Wong (2004) covering contracting management, conducted some investigations by using the logistic regression (LR) method. Granted that there are some techniques for risk propagation modeling such as Bayesian Network (BN) or artificial neural network (ANN), we attempted a different approach, namely logistic regression (LR), introducing another, previously unutilized tool that was deemed suitable for this study.

Based on the foregoing review, it can be stated that risk propagation modeling for construction projects has not been previously investigated to an appreciable degree, and new research, as presented herein, is justified and warranted. Thus, we decided to fill this gap by investigating risk propagation modeling among the engineering, procurement and construction phases of construction projects.

CHAPTER 3 - METHODOLOGY

3.1. Data Acquisition and Organization

Categorical variables were used in this research. In the beginning, raw data was acquired from some project management practitioners, reports, project documents, literature, and a state-of-the-art survey. Survey instruments were then prepared and distributed to collect information about risk factors and best practices regarding risk management implementation. Interviews were held with project managers, consultants, and contractors in the construction industry, and efforts were made to access unpublished information on their archives (hard copy, and on the internet open to public access). Risk management reports are the most commonly used documents in construction project management studies. In addition, project document reviews, expert judgments, and other information gathering techniques were used in this process. Further, relevant data were categorized by developing a new Risk Breakdown Structure (RBS) for the projects examined. Finally, a database was designed and developed based on the new RBS that was used in this research. The risk events for construction projects were classified into three main categories as engineering, procurement, and construction phases. We conducted two risk surveys focusing on risk propagation among the engineering, procurement, construction (EPC) phases and project management areas (PMA), requesting construction experts to participate in the surveys.

3.2. Risk Events (RE)

Binary (dichotomous) independent variables were formed from the data collected, and coded as 0 and 1, where 0 indicates a strong relationship and 1 indicates no relationship as indicated by the variable. In this study, forty risk events were identified as independent variables and grouped into engineering, procurement, and construction phases as shown in the follow tables:

Table 1 - Engineering Risk Events

Risk code	Risk Description
RE1	Design errors or omissions
RE2	Misinterpretation of technical documents
RE3	Error to update technical and project documents
RE4	Errors and omissions in shop drawings
RE5	Late design decisions and drawings
RE6	Inadequate quality planning
RE7	Inadequate resource planning
RE8	Inadequate budget estimation
RE9	Inadequate time scheduling
RE10	Unclear scope
RE11	Using BIM in design
RE12	Using lesson learned in design

Table 2 - Procurement Risk Events

Risk code	Risk Description
RP1	Errors in the bidding process
RP2	Selecting unskilled supplier and subcontractor
RP3	Contract gaps
RP4	Changing market conditions
RP5	Changing currency rate
RP6	Lead time change (material delivery)
RP7	Changing law or regulation
RP8	Inadequate change management process
RP9	Payment delay
RP10	Availability of resources for subcontractors

Table 3 - Construction Risk Events

Risk code	Risk Description
RC1	Differing site conditions
RC2	Scope and responsibility gaps between prime (contractor) and subcontractors
RC3	New user function or technology request by owner
RC4	Scope creep
RC5	Delay in decision making and approval
RC6	Contractor caused delay
RC7	Fast tracking or crashing for accelerating time schedule
RC8	Using wrong reference specs, codes or standards
RC9	Inadequate resource management
RC10	Unskilled employees
RC11	Inadequate site housekeeping (delivery and storage)
RC12	Union labor influence and labor strike
RC13	Owner’s organization and personnel change
RC14	Inadequate planning system
RC15	Job site security
RC16	Construction pollution and environmental degradation
RC17	Safety hazards
RC18	Unethical work practices

3.3. Project management areas (PMA)

The PMI (2013) in PMBOK (project management body of knowledge) book indicated that ten project management knowledge areas. In this research, the six project management areas were selected from PMI project management knowledge areas which are more important in construction projects. Also, we added the safety management which is very critical for construction stakeholders. Therefore, seven project management areas were used to form the dependent variables.

DV1: Scope Management

DV2: Time Management

DV3: Cost Management

DV4: Quality Management

DV5: Resource Management

DV6: Communication Management

DV7: Safety Management

In this research, binary logistic regression analysis was conducted by using SPSS software. Further, the binary dependent variables were coded as 1 for strongly affected and 0 for not strongly affected.

Although PMI (2013) in chapter nine of PMBOK discusses project human resource management, we decided to focus on resource management which covers the management of human resource, equipment, tools, and materials.

Also, the communication management includes two chapters of PMBOK; communication and stakeholder management.

3.4. The Surveys

There were many research questions in our study, and to address them we decided to establish two surveys for this investigation. We sent these surveys to two practitioner groups with similar abilities and backgrounds. Survey One focused more on the relationship among the phases of construction projects (engineering, procurement, construction), and we asked the participants to determine the impact of risk events on other phases of construction projects. In Survey Two, we asked the other group of participants to answer questions about the relationships that exist among risk events in different phases and project management areas.

3.5. Missing Data

If there is missing data for any variable that will be a problem in the multivariate analysis since that case will be excluded from the analysis. In this situation, we should use a substitution method so that we can retain enough cases to have sufficient power to interpret the result.

IBM SPSS Statistics 23 has a specific package for evaluating missing data called missing value analysis procedure. We focused on three key issues for evaluating such missing data: the number of cases missing per variable, the number of variables missing per case, and the pattern of correlations among variables created to represent missing and valid data. After evaluation, we ran the "imputation missing value" procedure to replace missing values for both surveys in this investigation.

The findings of the logistic regression analysis on the dataset are presented in Chapter Four of this dissertation.

3.6. Data Analysis

3.6.1. Univariate

The initial set of variables was based on the literature review, surveys and interviews with experts. Descriptive statistics were used to establish data demographics and find the frequencies of observations on each variable considered. In this study, the univariate analysis shows the demographics of the surveys' participants. The dependent variables are indication(s) of the level of education, experience, and roles of participants, as well as the type and capacity of their projects.

Additionally, we used two strong tools, sensitive analysis, and radar diagram, to identify the degree of each risk event (independent variable). They show the extent to which uncertain elements (risk events) affect objectives (other phases of construction projects) at the baseline. A tornado diagram is a method for sensitivity analysis data which displays the variables with the greatest effect on a project as horizontal bars.

3.6.2. Model

A Risk Propagation Model (RPM) was created as a predictive model to understand and analyze risk propagation behavior among the engineering (E), procurement (P), and construction (C) phases and project management areas (PMAs) in construction projects. After reviewing a variety of risk models, such as Artificial Neural Networks (ANN), Bayesian Networks (BN), the Risk Structural matrix (RSM), and the Structural Equations Model (SEM), we decided to focus on the logistic regression model as it is a statistical model that best meets our research objectives. Microsoft Excel and SPSS software were employed to analyze the computer-based data.

3.6.3. Suggested Model

After reviewing different risk models, we chose to focus on a special class of models called the logistic regression model which is a statistical model that can depict propagation among the engineering, procurement, and construction (EPC) phases and project management areas (PMA) in construction projects. There are multiple reasons for our choice. First, we needed a robust class of models on which to demonstrate and apply our ideas, as well as to evaluate the resulting algorithms. Second, a logistic regression model is an expert system model, and practitioners can use this tool. Third, we are interested in deriving cause-effect relationships from data. Finally, although the logistic regression analysis has been found to be very robust without strongly adhering to this assumption, as Sharma (1996) stated, other multivariate statistical methods require a normality assumption, which is difficult to satisfy in practice. In this study, the dichotomous variable collection facilitated the forecasting process and simplified a robust logistic regression computation.

3.6.4. Logistic Regression Model

Linear regression (a discrete time model) can be used to predict the risk of an event within a certain time period. One of the linear regression modeling approaches is a logistic regression (or logit regression, or logit model) which explains the nonoccurrence or occurrence of an event. The logistic regression model has been used in epidemiology (Steyeberg et al. (2001), Kleinbaum (1994)); transportation safety (Bham et al. (2012), Yingfeng and Yong (2008), Yang et al. (2012), Gom et al. (2013)), and marketing research (Condon (2012)); as well as in a variety of construction management and safety related studies (Huang (2003), Fang et al. (2006), and Li (2006)).

Hosmer and Lemeshow (2000) described the objective of the logistic regression analysis as the most parsimonious selection and the best fitting model to describe the relationship between a set of independent (input or predictor) variables and a dependent variable (outcome or response variable). Additionally, Kleinbaum et al. (1994) explained that the logistic regression method does not have the requirements for the independent variables to be linearly related or normally distributed. Thus, the logistic regression can be used for modeling when the dependent variables are categorical and dichotomous if the independent variables are continuous or categorical.

The regression model can be depicted by

$Y = \beta_0 + \beta_1.X_1 + \beta_2.X_2 + ... +\beta n.Xn$

Where,

Y is the dependent variable with a value of 0 or 1;

X_1 through X_n are the independent variables;

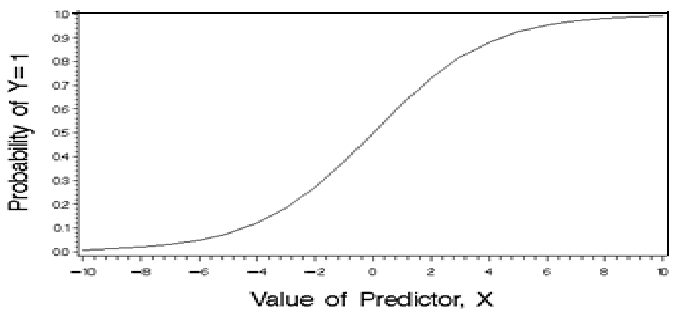
β_0 is a constant;

β_1 through β_n are the regression coefficients.

In logistic regression, the variable odds ratio represents how the odds change with a one unit change in that variable holding all other variables constant. In other words, a negative for a beta coefficient implies a decrease in Y, while a positive sign means an increase in Y.

Hulya et al. (2013) described how logistic regression evaluates the relationship among the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function, which is the cumulative logistic distribution function of the S shape where the probability must lie between 0 and 1 as seen in Figure 10.

Figure 10 - Logit Function



It is important to understand the relationship between probability and the independent variables that are nonlinear in a logit function, but the relationship of the log odds and the independent variables is linear.

A logit function can be expressed as the probability of the occurrence of an event by

$$P(Y = 1 \mid X_{1\ldots n}) = \frac{1}{1 + e^{-Y}} = \frac{1}{1 + e^{-(\beta 0 + \beta 1.X1 + \beta 2.X2 + \ldots + \beta n.Xn)}}$$

When the non-occurrence becomes

1 - P(Y=1| X1...n) = P(Y=0 | X1...n)

The joint effects of all independent variables on the odds of the occurrence of an event can then be denoted as

$$\text{odds} = \frac{P(Y = 1|X_{1....n})}{1 - P(Y = 1|X_{1....n})} = e^{\beta_0 + \beta_1.X_1 + \cdots + \beta_n.X_n}$$

Since the dependent variable is dichotomous, its value can be either 0 or 1; however, unlike the linear regression case, it is not normally distributed. Thus, in order for it to have a normal distribution, a "logit" transformation is necessary. The logit transformation can proceed as

$$\text{logit (odds)} = \ln\left(\frac{P(Y = 1|X_{1....n})}{1 - P(Y = 1|X_{1....n})}\right)$$

Or

$$\ln\left(\frac{P(Y=1|X_{1....n})}{1-P(Y=1|X_{1....n})}\right) = \ln(e^{\beta_0+\beta_1.X_1+\cdots+\beta_n.X_n}).$$

Thus, the logistic regression equation becomes

$$\ln\left(\frac{P(Y=1|X_{1....n})}{1-P(Y=1|X_{1....n})}\right) = \beta_0 + \beta_1.X_1 + \beta_2.X_2 + \ldots + \beta_n.X_n$$

A "Wald test" statistic is utilized to test the joint statistical significance of regression coefficients (β) in the logistic regression model. It is calculated as:

$$\text{Wald} = \frac{\beta^2}{SE_\beta{}^2}$$

Also, whereas the model is considered as a whole, the exponential beta (Exp (β)) represents the odds ratio for each explanatory variable taken as a dichotomous dummy variable. As previously indicated, confidence intervals must exclude 1 or 0.

Obviously, the forecasting ability must be validated for every logistic regression model. However, validation pertains to the agreement between the observed and predicted outcomes. It may be possible that the model validity can be examined by studying the residuals and defined as the difference between the observed and predicted results.

In this study, the degree of association on project management areas was adopted as the dependent (outcome) variable for logistic regression, and the independent (predictor) variables found significant were incorporated in the regression analysis. Thus, the validation of the model was confirmed by dividing the data into two portions 75% and 25%. In other words, the accuracy of 75% of the model was examined by randomly using the data from the other 25% part of the data set.

3.6.5. SPSS Analysis Model

There are a variety of methods to input variables into SPSS software and run a logistic regression analysis. In this study for the variable insertion, the backward stepwise (LR) method was utilized. In the backward stepwise (LR) method, all the predictor variables were inserted into the model in the first step of the analysis. Then, the insignificant variables were taken out, based on the aforementioned statistical criterions, until all the significant variables remain in the model.

In this study, Wald Chi-squared significance values below 5% signified statistical significance. Additionally, we used the contingency tables for the Hoshmer and Lemeshow test for the predictor model's goodness of fit, with p values greater than 5% indicating a good fit. Also, the SPSS output tables show us the overall fit of the best model which was evaluated by the model log likelihood statistic.

3.6.6. Model Validation

Giancristofaro and Salmaso (2003) explained that the logistic regression model validation is essential to calculate the outcomes and performance of the model. When a model is not validated, the future outcomes will be predicted inaccurately and unreliable.

There are two techniques to validate a logistic regression model: internal validation and external validation.

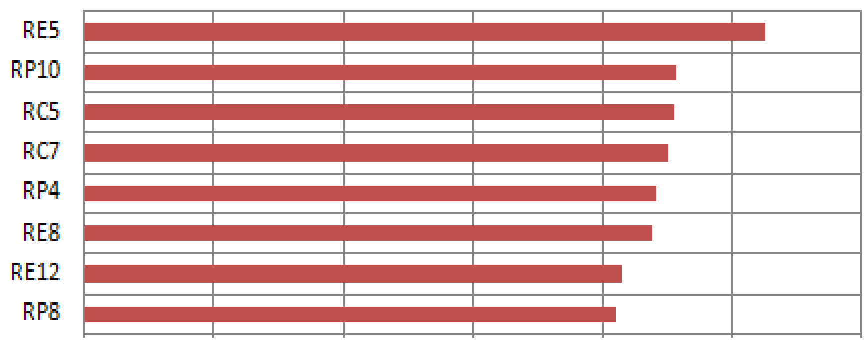
Internal validation is conducted by splitting the dataset in a certain ratio, which is usually 80/20, 75/25 or 70/30. Next, the model should be developed for the bigger portion of the dataset. Then, the mentioned model is applied to the smaller portion of the dataset. Finally, the accuracy of the result is measured and verified.

In external validation, a logistic regression model is developed separately based on a new sample set of data. Then, the old model and the new model are measured and compared to each one.

In this study, the internal approach was selected to validate our fitted models. Since our sample size is sufficiently large, the data was split into two data sets in a 75/25 ratio. To facilitate a selection of cases, we used the random sample of cases featuring the SPSS software which takes the values of 0 and 1. SPSS assigned the value of 1 randomly to 75% of the cases which we used to develop the model, and the remaining 25% was used to validate this data.

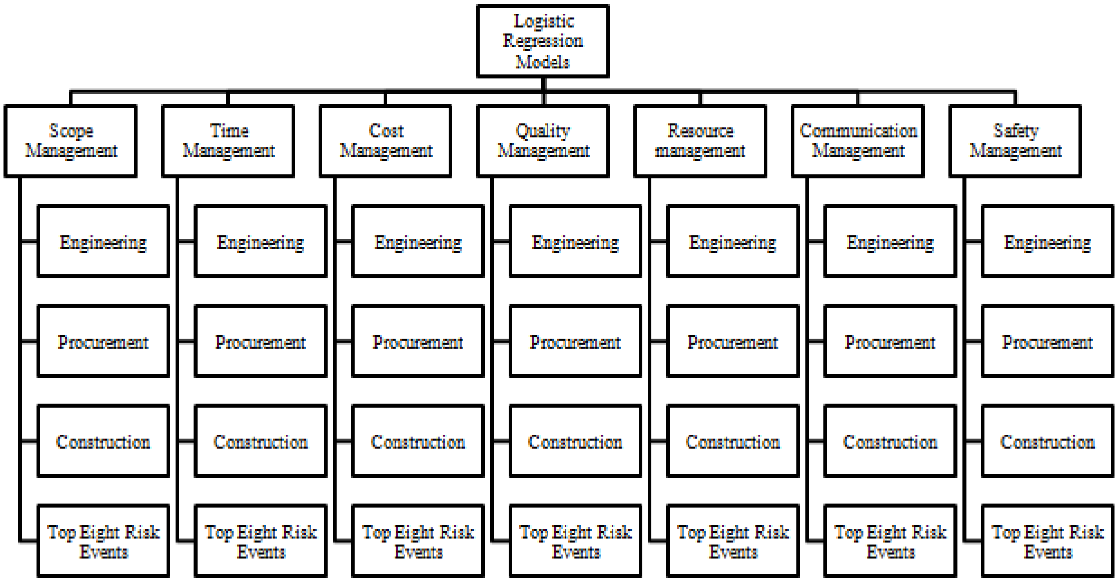
In this study, the seven project management areas represent our dependent variables. We have forty independent variables (risk events) which were divided into engineering (twelve), procurement (ten), and construction (eighteen) phases. Thus, we developed a model for every phase, or rather we can say we developed three models for every project management area; therefore, we created at a total of 21 models. The Pareto principle (also known as the 80–20 rule) indicates that “for many events, roughly 80% of the effects come from 20% of the causes”. Figure 11 indicated the 8 top risk events which are RE5, RP10, RC5, RC7, RP4, RE8, RE12, and RP8. Therefore, we used that rule and separated 20% of top risk events (a total of 8 top risk events) from the results of Survey One and developed seven models for the risk management areas.

Figure 11 - Top 8 Risk Events



In sum, a total of twenty-eight different models were developed for this research study by separating the entire dataset into subsets to understand which risk events are most important in construction projects. Figure 12 displays the models that were developed.

Figure 12 – Developed Logistic Regression Model



AS we explained previously, in this research, we have seven dependent variables and the sample size for each dependent variable is 241 cases (7×241=1687 answers). The cases of each dependent variable were randomly split into 181 cases for developing the models (as 75% of data set) and 60 cases (as 25% of data set) for validation.

CHAPTER 4 - RESULT AND ANALYSIS

4.1. Survey One Analysis

Survey One was developed to analyze the relationship among the risk events in engineering, procurement, and construction phases of construction projects. The participants invited to answer the questions online via SurveyMonkey website, which is an online survey development cloud-based company.

4.1.1. Univariate Analysis

In the Survey One, we invited many experts and practitioners who had good experience and education ability to answer our research questions of the survey. In this section, we clarified background of 103 participants in Survey One by using univariate analysis as follow:

Figure 13 shows the educational background of the 103 people participated Survey One. Also, the graph shows that more than 92% have 4 years or more college experience.

Figure 13 - Education Background of Participants

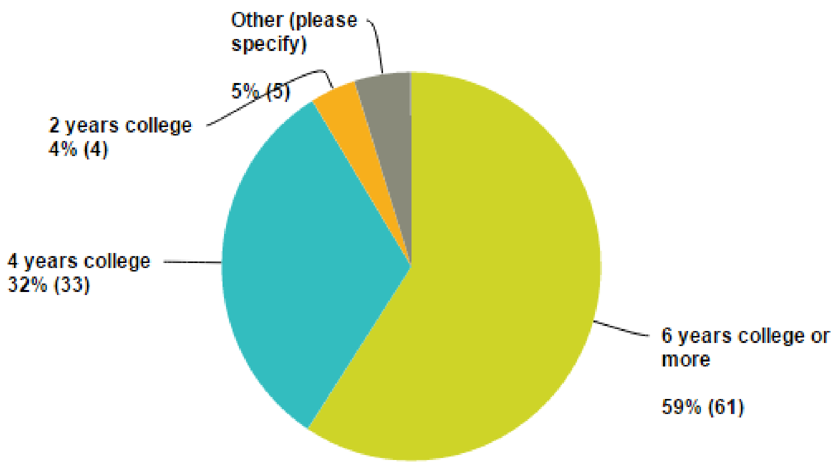


Figure 14 shows the project experience background of 103 people who participated in Survey One. The graph shows that more than 86% have a minimum of 5 years of experience working on projects.

Figure 14 - Experience Background of Participants

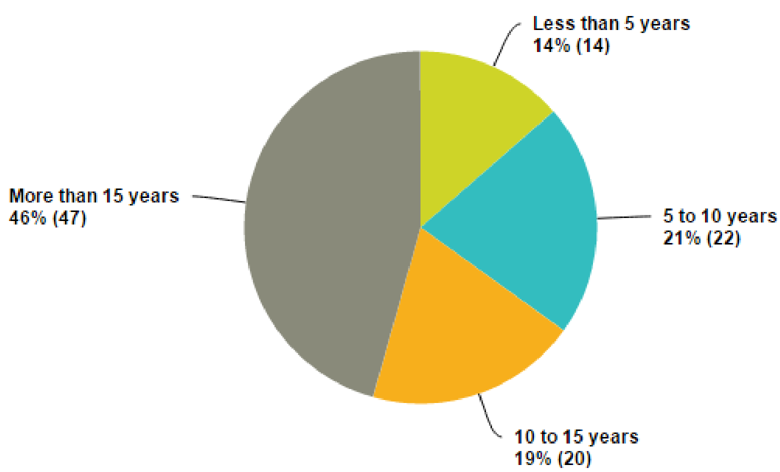
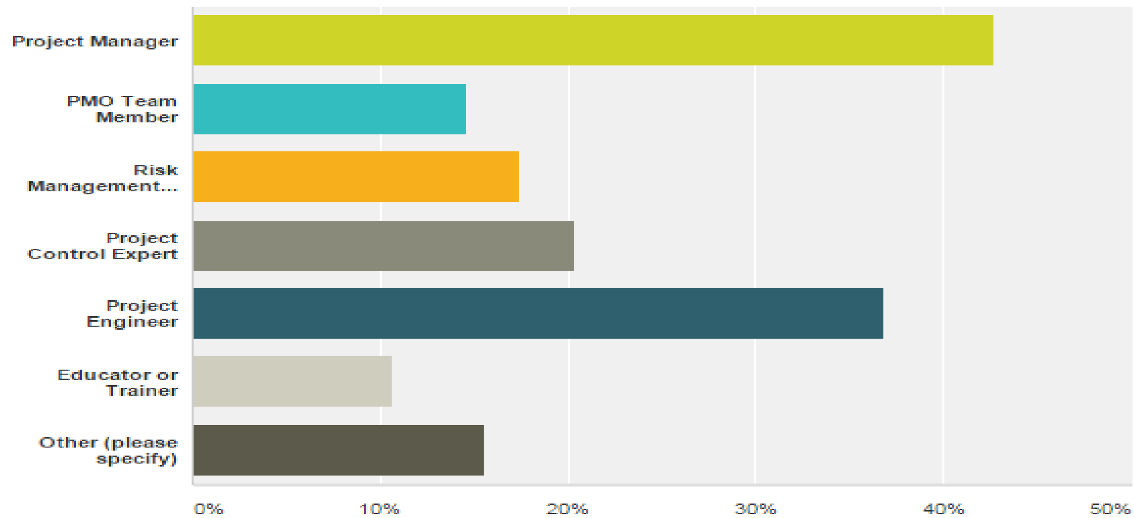


Figure 15 shows the typical roles of the 103 people who participated in Survey One. It shows that more than 40% hold the position of project manager.

Figure 15 - Background of Participants: Roles



According to Figure 16, we can see the average value the projects (millions of dollars) which participants work in based on Survey One.

Figure 16 - Background of the Participants: Project Dollar Value in Million

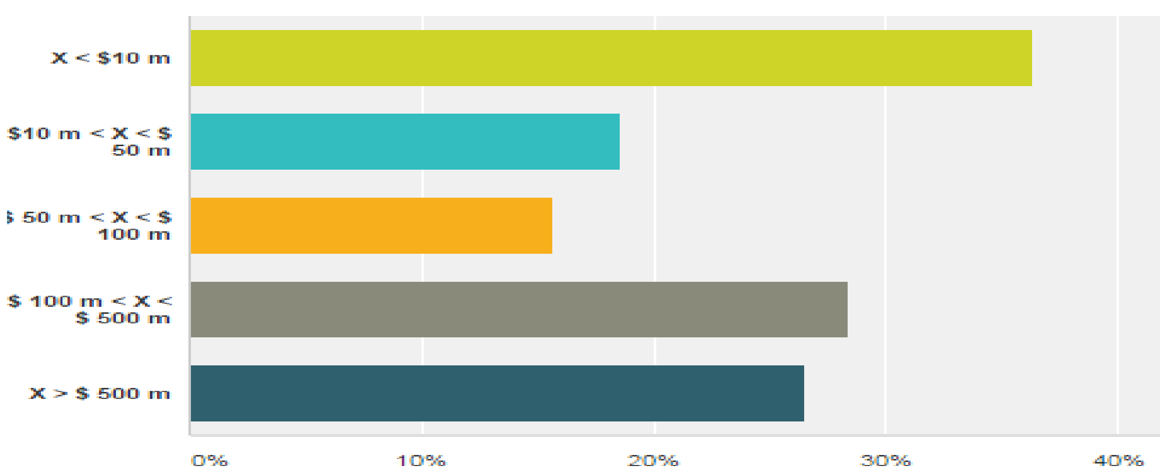


Figure 17, we can see the project type distributions according to Survey One. Approximately 41% of participants have experience working on industrial projects, which are the most complicated type of construction projects.

Figure 17 - Background of Participants: Project Type

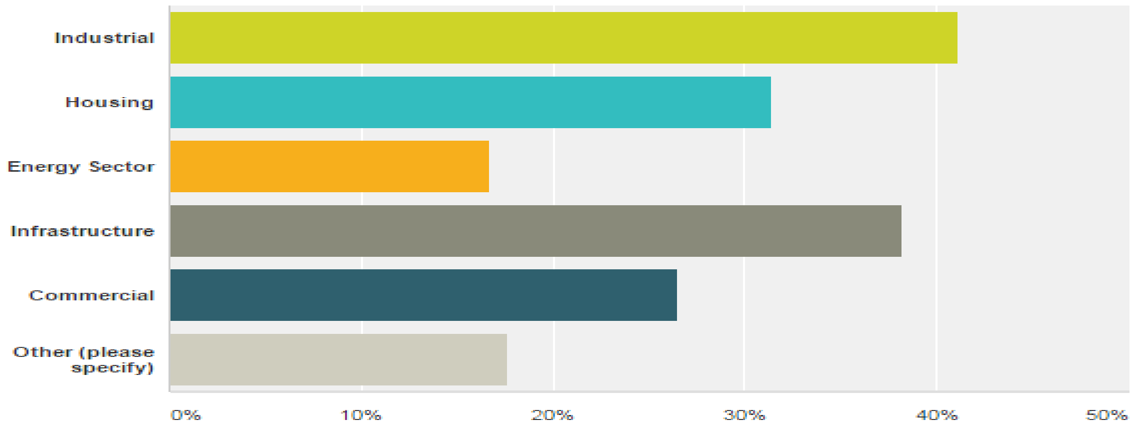
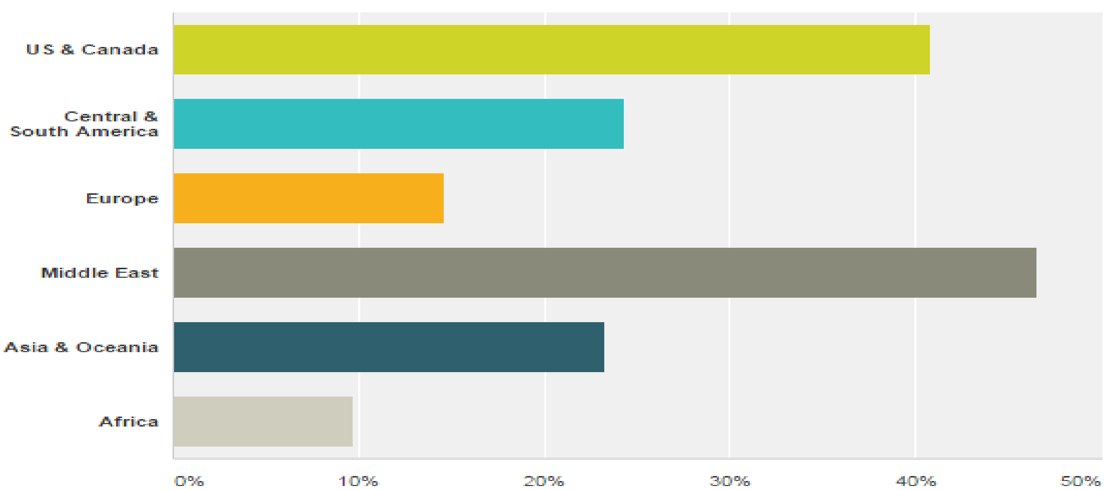


Figure 18 shows the project location distributions in the world based on respondents to Survey One. Approximately 46% of responders have experience in Middle Eastern countries more than 40% have experience in U.S. and Canadian projects.

Figure 18 - Global Scattering of Participants



4.1.2. Risk Propagation Analysis

In this section, risk propagation was analyzed by expressing a new series of equations to measure and analyze risk events. In this regard, we introduced new definitions such as probability factor (PF), impact factor (IF), and the score of risk propagation, defined as follows:

<u>Probability Factor (PF):</u>

PF was calculated based on the probability of each risk factor as explained below:

$$\mathbf{PF_r = \Sigma\, W_i \times P_r}$$

Where,

PF_r: Probability Factor of risk event r

r: Risk event; r = 1, 2, …, 40

P_r: Probability percentage of risk event r

W_i = Weight factor assigned to each response category,

i: Response of probability category factor

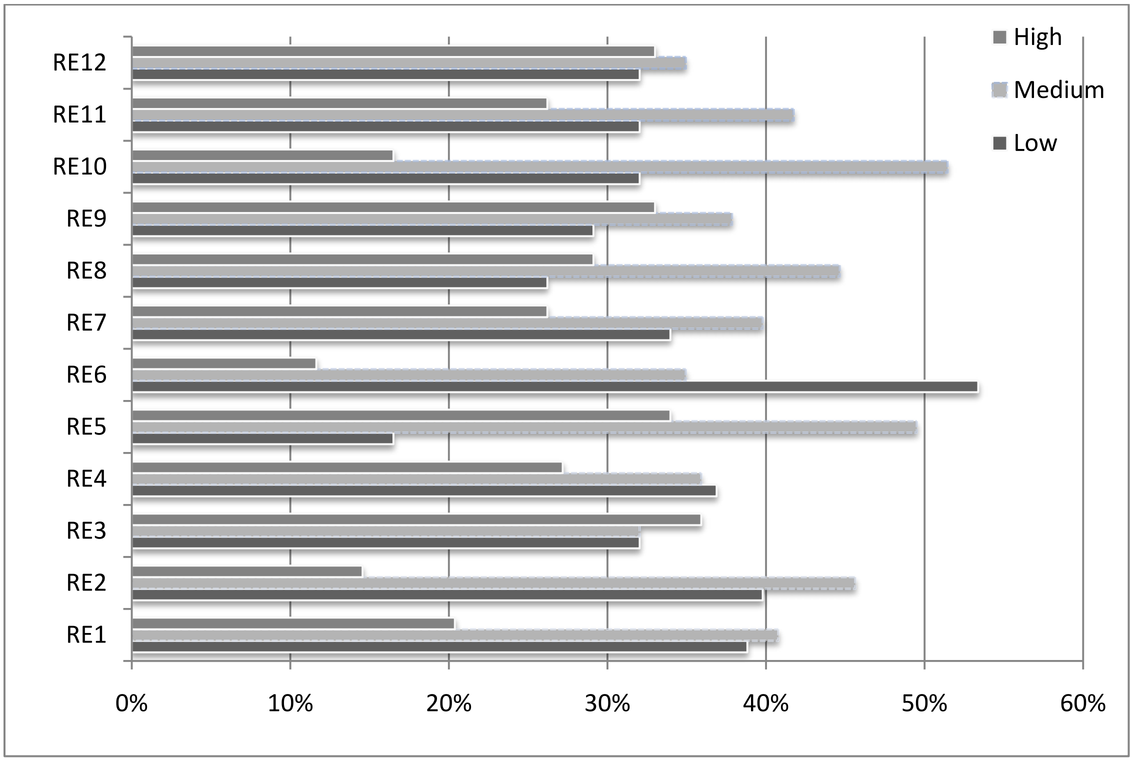
In Survey One, we had three options: Low, Medium, and High. The weight factors were assigned as shown in Table 4:

Table 4 - Probability Weight Factor

Probability category factor ($_i$)	Lower Limit	Upper Limit	Mean	Weight factor (W_i)
Low	0.00%	33.33%	16.66%	1
Medium	33.33%	66.66%	50.00%	3
High	66.66%	100.00%	83.33%	5

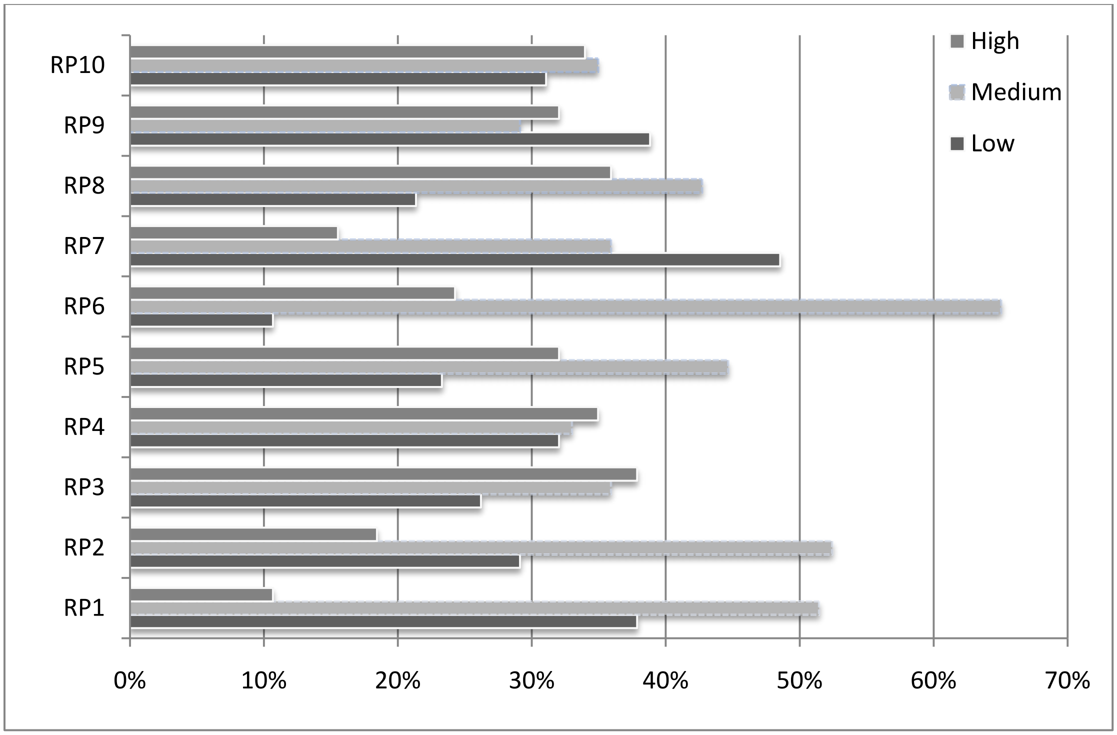
Based on the results of Survey One, Figure 19 displays the probability percentage (P_r) of the twelve engineering risk events in the engineering phase of construction projects (See Table 1 for the name of the construction risk events). As one can see, the data was classified into three categories: Low, Medium, and High.

Figure 19 - Probability of Engineering Risk Events



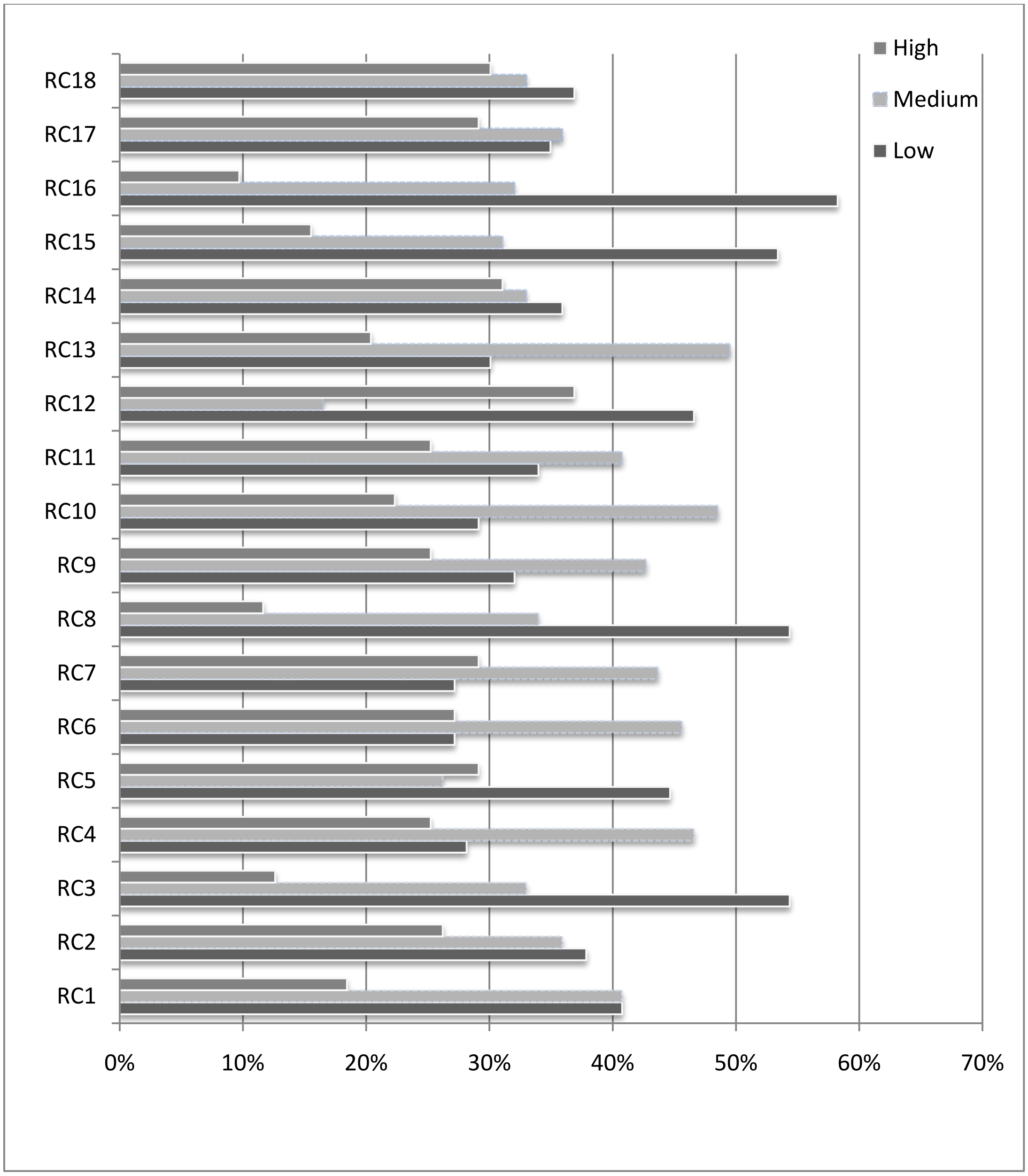
Based on the results of Survey One, Figure 20 displays the probability percentage (Pr) of the ten procurement risk events in the procurement phase of construction projects (See Table 2 for the name of the procurement risk events). As one can see, the data was classified into three categories: Low, Medium, and High.

Figure 20 - Probability of Procurement Risk Events



Based on the results of Survey One, Figure 21 displays the probability percentage (Pr) of the eighteen risk events in the construction phase (See Table 3 for the name of the construction risk events). As one can see, the data was classified into three categories: Low, Medium, and High.

Figure 21- Probability of Construction Risk Events



<u>Impact Factor (IF):</u>

Impact factor (IF) was calculated based on the risk event impact on another phase of project (E, P and C) as follows:

$\mathbf{IF_r = \Sigma\Sigma\ W_j \times I_{rk}}$

Where,

IF_r: Impact Factor of risk event r

r: Risk event; r = 1, 2, …, 40

k: Phase of the construction project (E, P or C)

$\mathbf{I_{rk}}$: Impact percentage of risk event r on phase k

W_j: Weight factor assigned to each response category (option),

j: Response of impact category factor

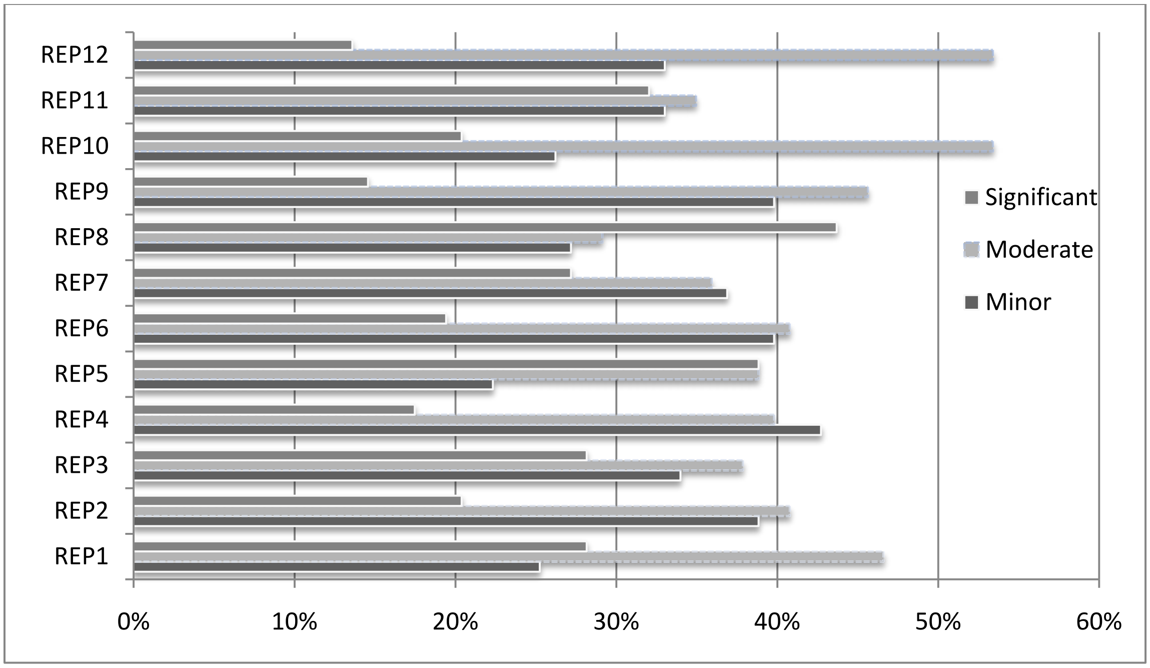
In Survey One, we had three options: Minor, Moderate, and Significant. The weight factors were assigned as shown in Table 5:

Table 5 - Impact Weight Factor

Impact category factor ($_j$)	Lower Limit	Upper Limit	Mean	Weight factor (W_j)
Minor	0.00%	33.33%	16.66%	1
Moderate	33.33%	66.66%	50.00%	3
Significant	66.66%	100.00%	83.33%	5

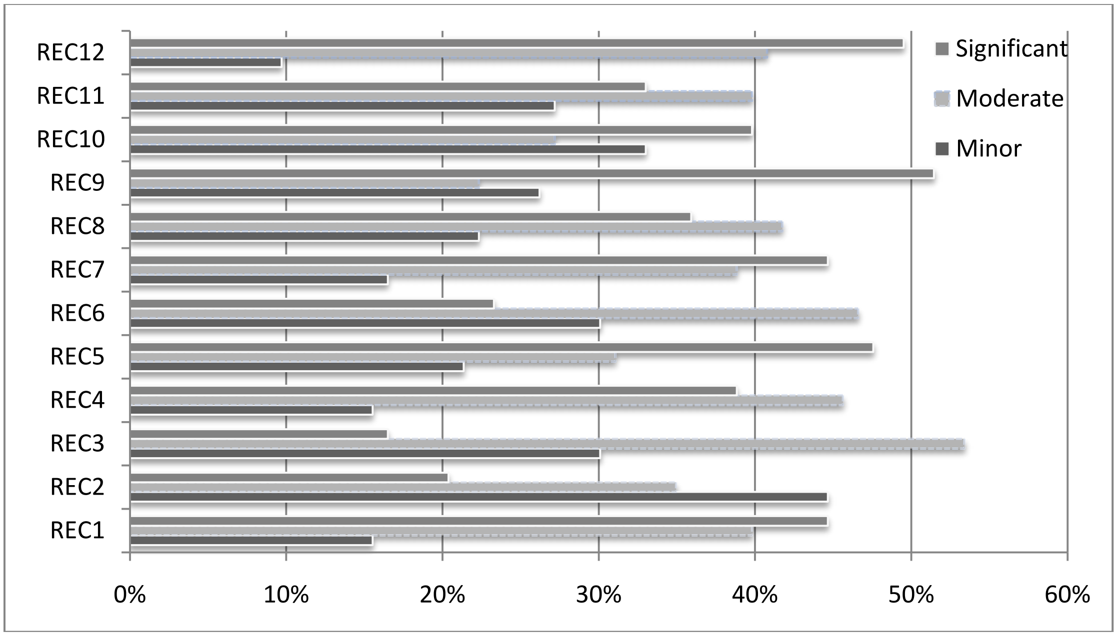
According to the results of Survey One, Figure 22 shows the impact percentage (Ir) of twelve engineering risk events on the procurement (P) phase of construction projects (See Table1 for the name of the engineering risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 22 - Impact of Engineering Risk Events on the Procurement Phase



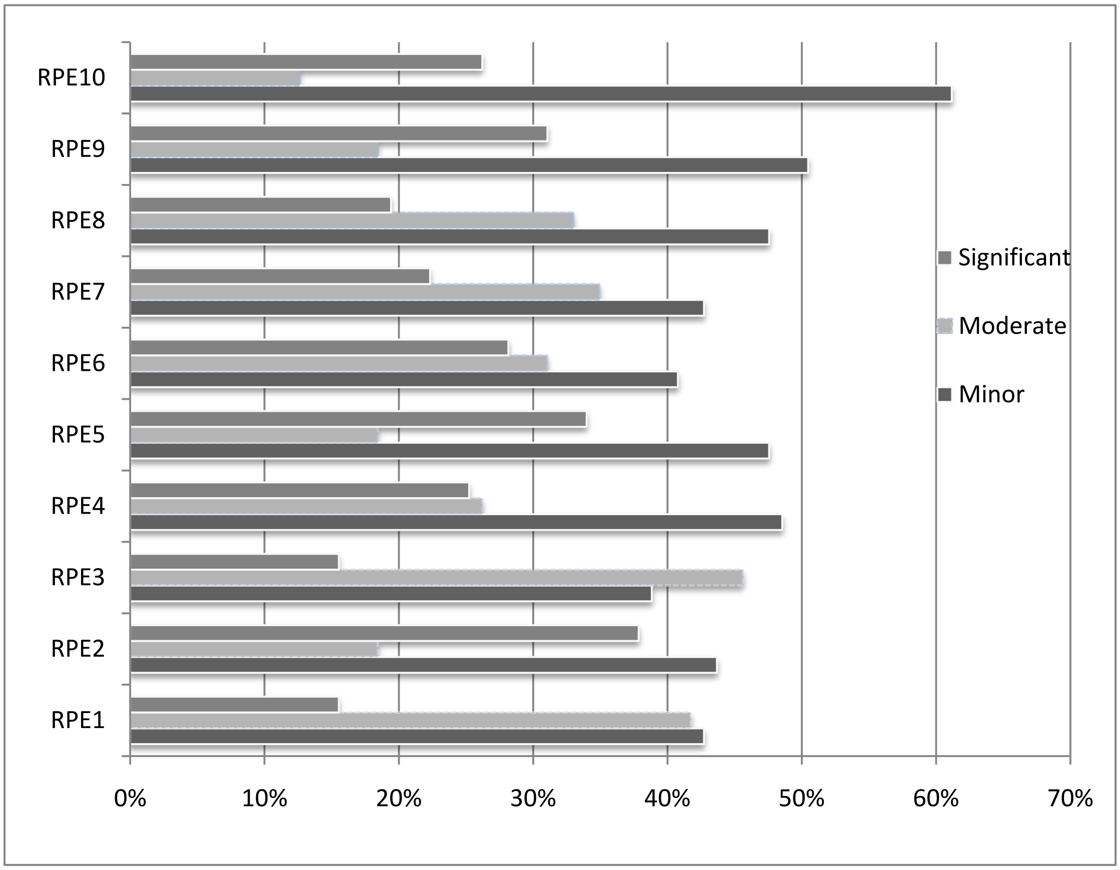
According to the results of Survey One, Figure 23 shows the impact percentage (Ir) of twelve engineering risk events on the construction (C) phase of construction projects (See Table1 for the name of the engineering risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 23 - Impact of Engineering Risk Events on the Construction Phase



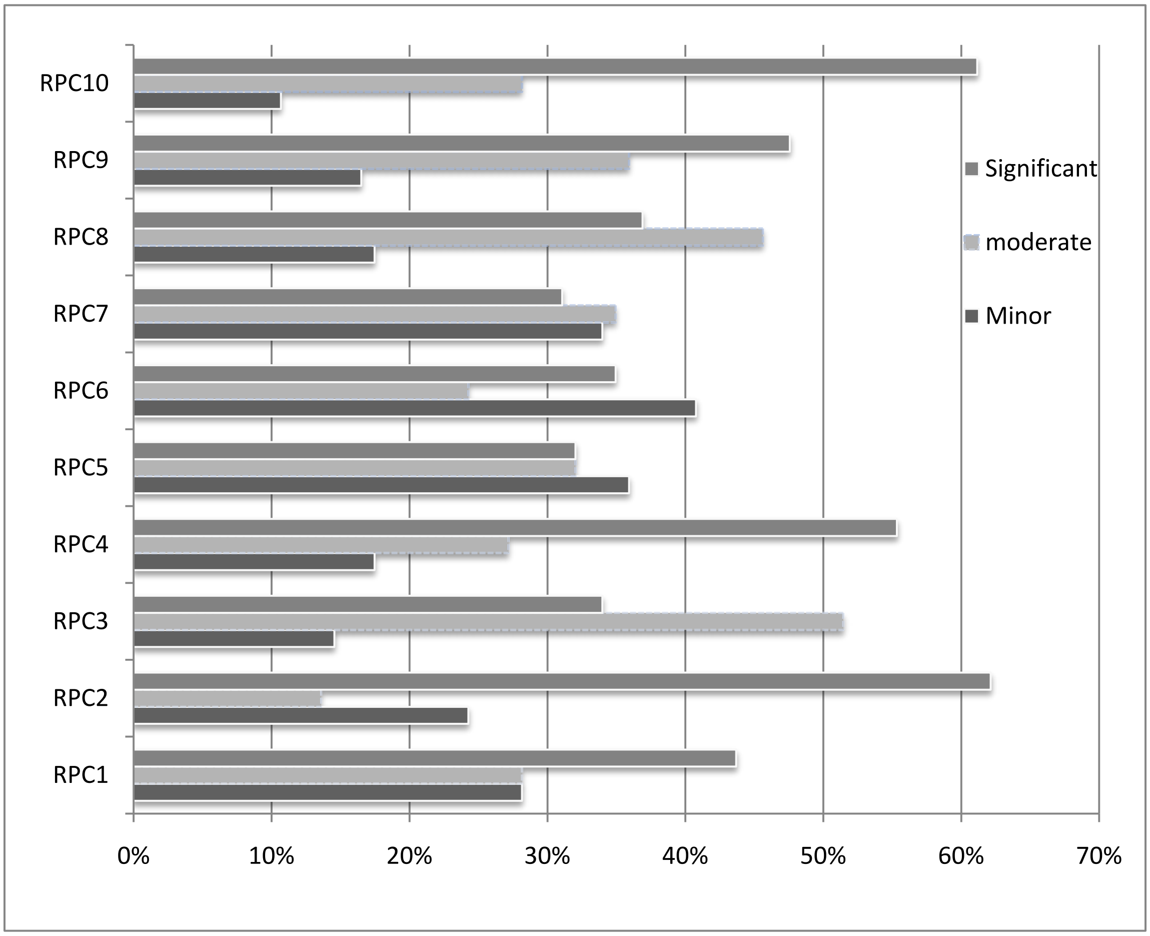
According to the results of Survey One, Figure 24 shows the impact percentage (Ir) of ten procurement risk events on the engineering (E) phase of construction projects (See Table2 for the name of the procurement risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 24 - Impact of Procurement Risk Events on the Engineering Phase



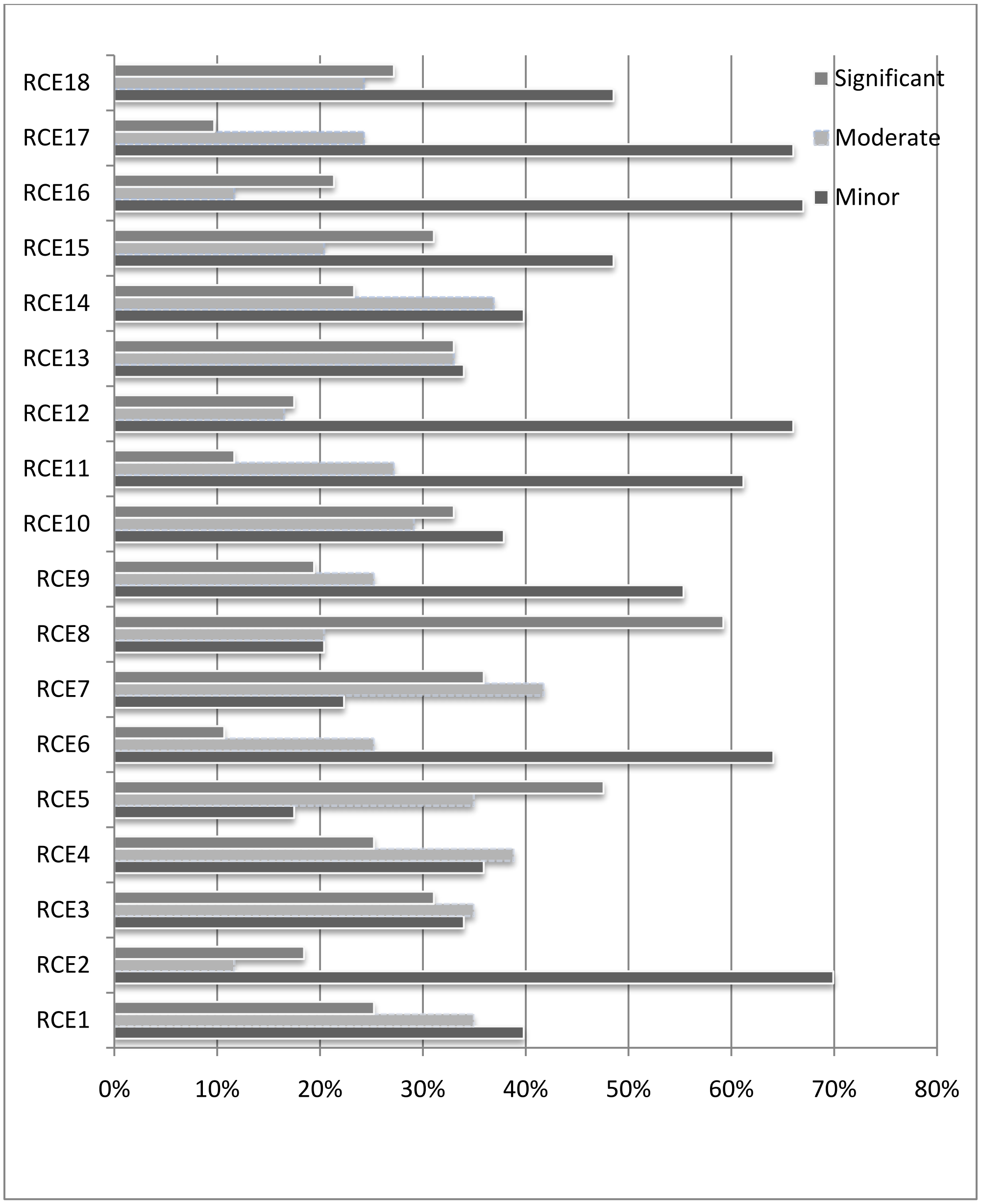
According to the results of Survey One, Figure 25 shows the impact percentage (Ir) of ten procurement risk events on the construction (C) phase of construction projects (See Table2 for the name of the procurement risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 25 - Impact of Procurement Risk Events on the Construction Phase



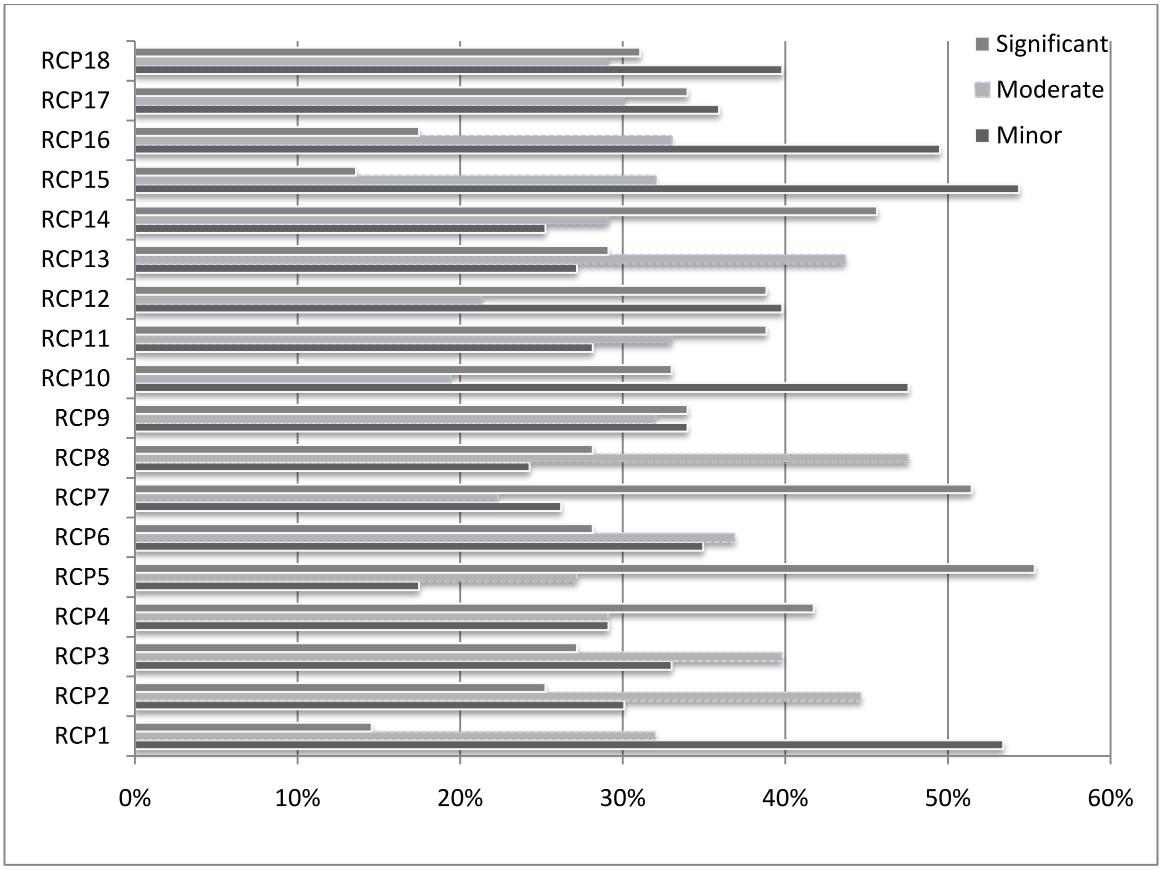
According to the results of Survey One, Figure 26 shows the impact percentage (Ir) of eighteen construction risk events on the engineering (E) phase of construction projects (See Table3 for the name of the construction risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 26 - Impact of Construction Risk Events on the Engineering Phase



According to the results of Survey One, Figure 27 shows the impact percentage (Ir) of eighteen construction risk events on the procurement (P) phase of construction projects (See Table3 for the name of the construction risk events). As one can see, the data was classified in three categories: Minor, Moderate, and Significant.

Figure 27 - Impact of Construction Risk Events on the Procurement Phase



4.1.3. Sensitivity analysis

Sensitivity analysis studies the influence on the output of a model with varying input values. Since the results provided by outcomes of surveys are sometimes not easy to analyze, sensitivity analysis can extract the cause and impact relationship between the inputs and outputs of a developed model. It identifies the degree to which each independent (input) variables contributes to each dependent (output) variables. In fact, it shows the extent to which uncertain elements affect objectives at the baseline. A tornado diagram is a method for sensitivity analysis data. It displays the variables with the greatest effect on a project as horizontal bars.

<u>Score of risk event (S_r):</u>

S_r is Score of risk event r that is measured as follow:

$$\mathbf{S_r = PF_r \times IF_r}$$

PF_r: Probability Factor of risk event r

IF_r: Impact Factor of risk event r

Thus, based on calculated scores, we answered research question 4 which asked that how can the top risk propagation events be ranked based on their probability and impact on different construction project phases. Thus, we ranked twelve engineering risk events and used a tornado diagram and radar diagram as shown Figure 28 and Figure 29. The risk events were divided into two parts; 10 negative risk events (threats) and 2 positive risk events (opportunities), and we did a sensitive analysis of them as follow.

Figure 28 - Engineering Risk Events Tornado Diagram

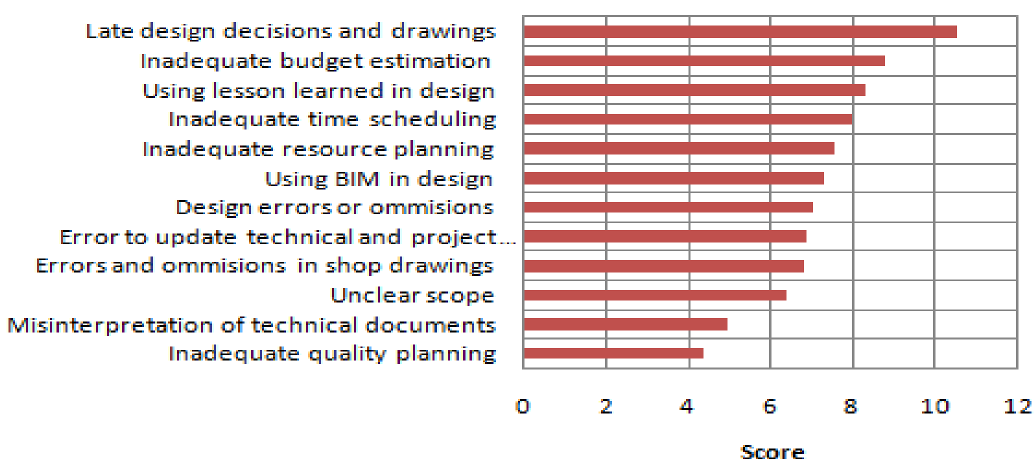
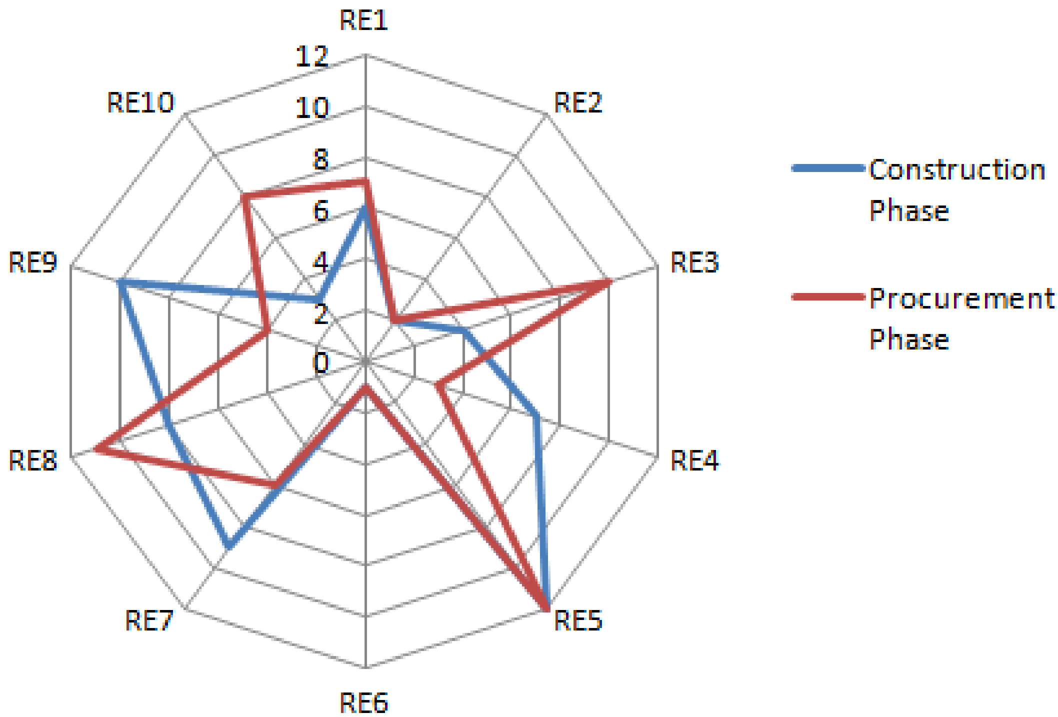


Figure 29 – Engineering Risk Events Radar Diagram



As one can see, “Late design decision and drawings” (RE5) is the most dangerous risk of an engineering phase and one which has the greatest impact on other phases (procurement and construction phases).

Also, based on calculated scores, we ranked ten procurement risk events. Then, a tornado diagram (Figure 30) and a radar diagram (Figure 31) show the procurement risk event ranking.

Figure 30 - Procurement Risk Event Tornado Diagram

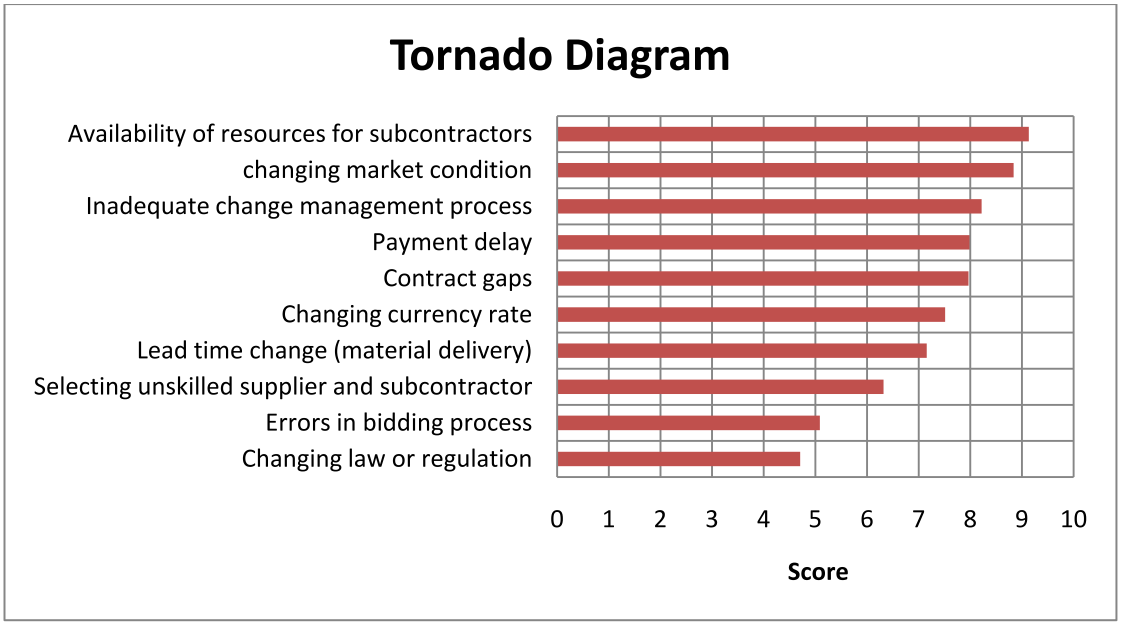


Figure 31 - Procurement risk Events Radar Diagram

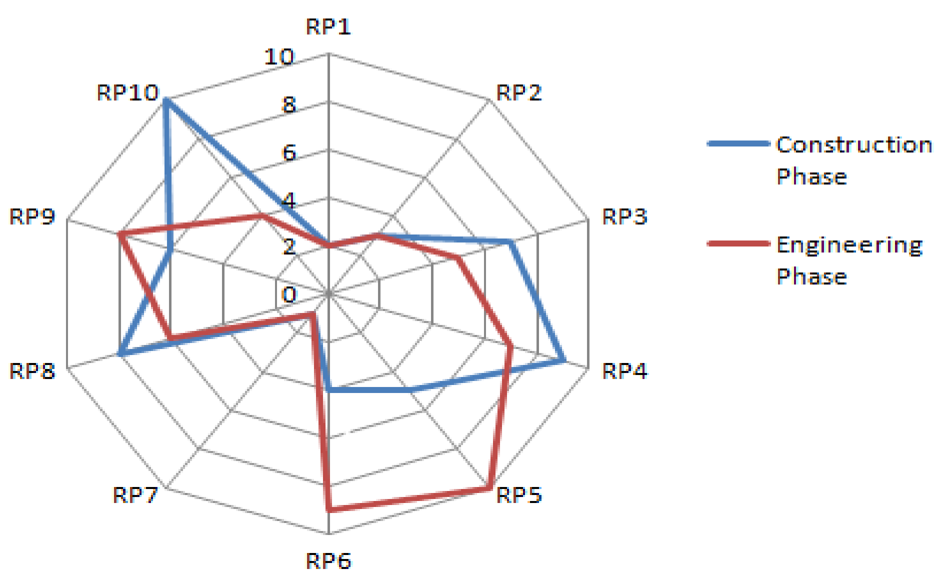


Figure 30 indicated that “Availability of resources for subcontractors” (RP10) has the greatest impact on other phases (engineering and construction phases).

Further, based on calculated scores, we ranked eighteen risk events of the construction phase. Thus, the tornado diagram below (Figure 32) and radar diagram (Figure 33) display the construction risk event ranking.

Figure 32 - Construction Risk Event Tornado Diagram

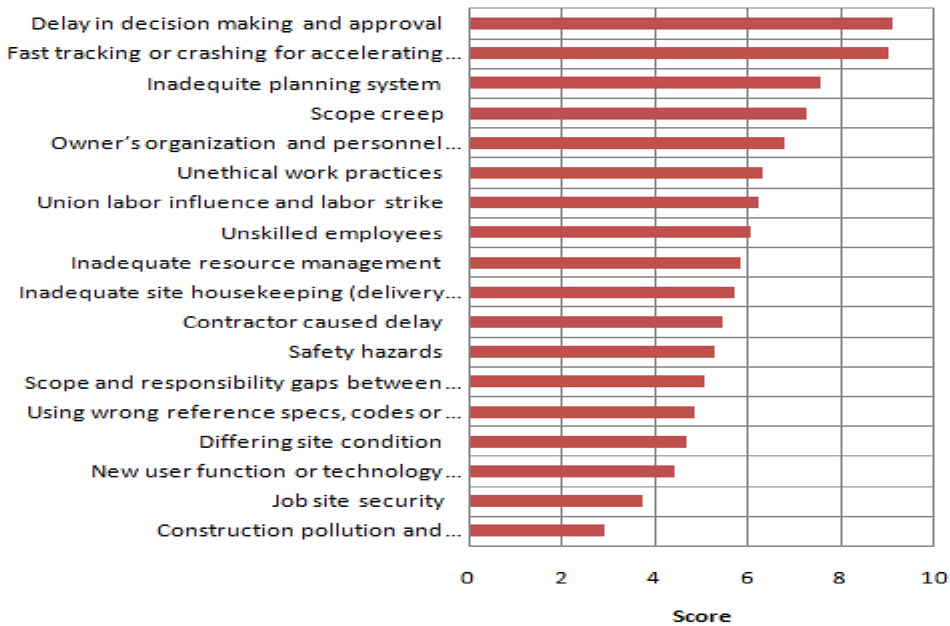


Figure 33 - Construction Risk Events Radar Diagram

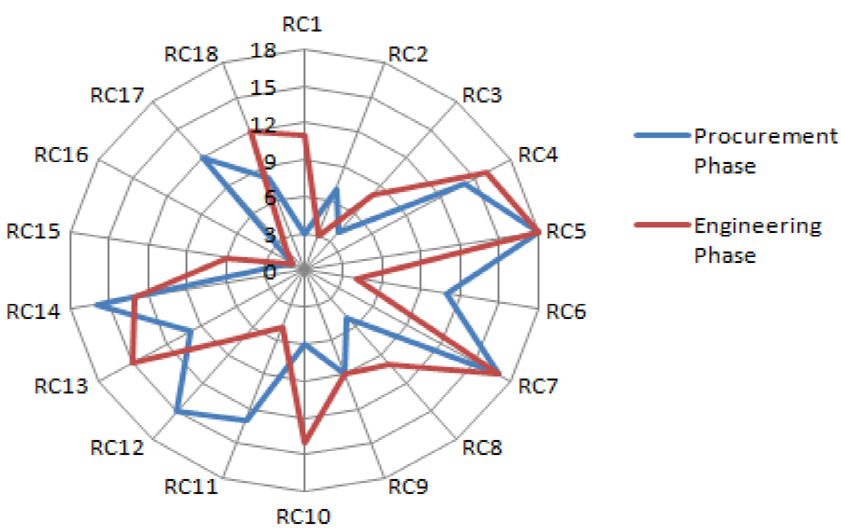
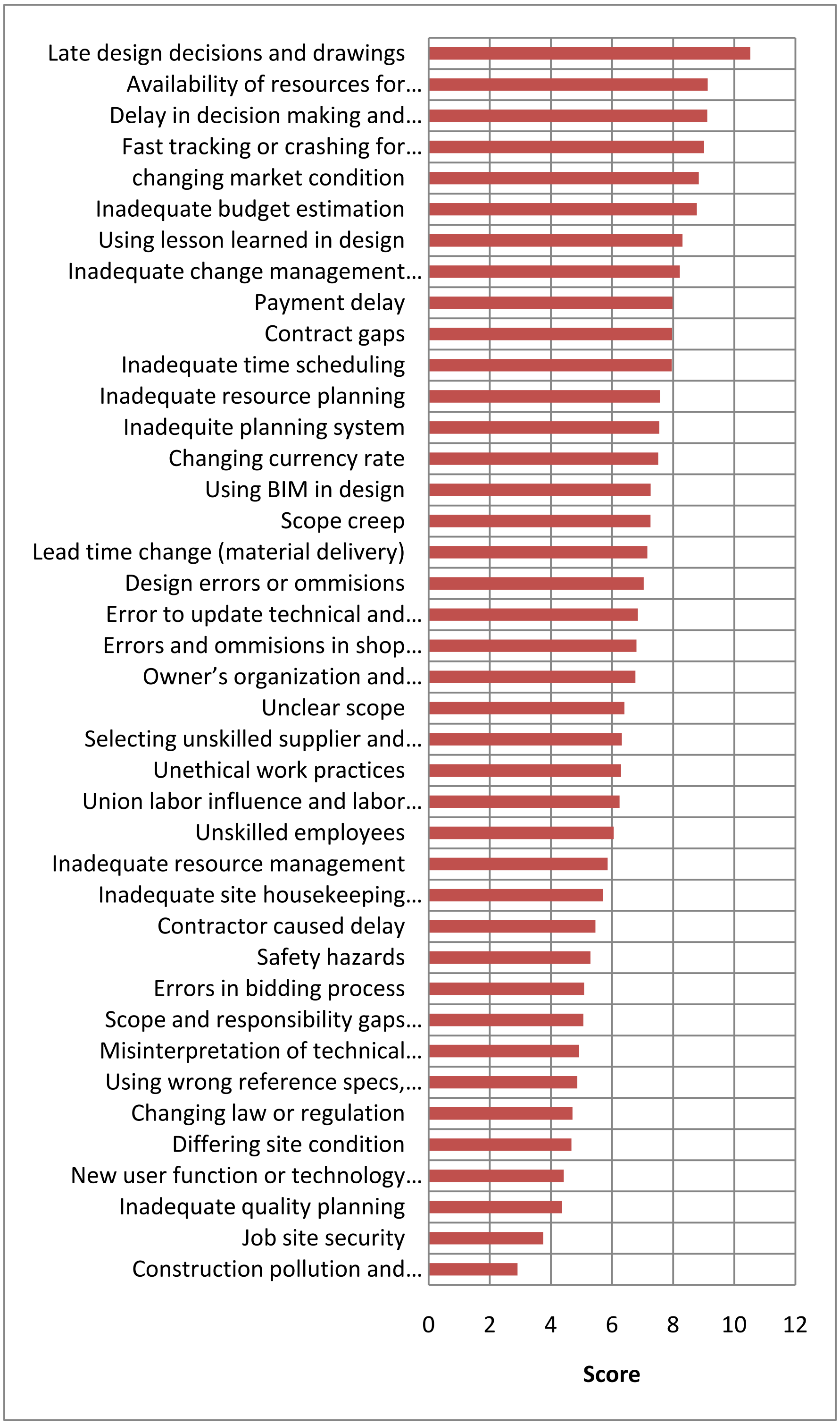


Figure 32 indicated that "Delay in decision making and approval" (RC5) has the greatest effect on other phases (engineering and procurement phases).

Finally, overall forty risk events were ranked as shown in Figure 34. According to this sensitive analysis, "late design decisions and drawings" (RE5) is the most important risk event in terms of risk propagation to other phases of construction projects.

Based the Pareto principle, mentioned in Chapter Three, 20% of the top risk events from that tornado diagram (equal 8 from 40 risk events) were selected, and they were used to develop seven binary logistic regression models that we will discuss later in this chapter. Therefore, project managers and their teams should be careful about the 8 top risk events and the potential impacts of transmitting them to other phases.

Figure 34 - Overall Risk Events Tornado Diagram



Score of propagation phase (S_{x-y})

There is no doubt that two terms are very critical to explain phase propagation among phases of construction projects: source phase and target phase. Let us illustrate them with an example. When we investigate risk propagation between the engineering (E) phase and the procurement (P) phase, there are two interrelationships between the E and P; E-P and P-E. In the E-P relationship, the E is source phase and the P is target phase. Obviously, the positions of the phases are reversed for the P-E connection and the P is the source phase and the E is the target phase.

Thus, the score of x-y (S(x-y)) is the average of score of the risk events (Sr) which exist at phase x. In other words, the equal probability factor of risk events in the source phase (x) is multiplied by their impact factor in the target phase (y).

To answer the research question 6 (What is the highest ranked phase propagation based on the impact and probability study in a construction project?), the score of propagation risk events (S(x-y)) were measured as follows:

$$\mathbf{S_{(x-y)} = Average\ (S_r) = \Sigma\ PF_r \times IF_{ry}} \div N_x$$

- $S_{(x-y)}$: Score of propagation risk events from phase x to phase y
- S_r: Score of risk event r
- PF_r: Probability Factor of risk event r
- IF_{ry}: Impact Factor of risk event r on target phase y
- N_x: Number of risk events in source phase x

As with the previous assumption, there are three phases (engineering (E), procurement (P) and construction (C)) in construction projects. Thus, there are six relationships among the phases.

Based on calculated propagation scores, we did a sensitive analysis and ranked six relationships in a tornado diagram (Figure 35). Also, Figure 36 shows the demographic relationships among the E, P, and C phases in construction. It is clear that P-C is the strongest risk event propagation relationship in construction projects. In other words, procurement risk events have the greatest impact on the construction phase. As one can see, the scores of C-P and E-P are equal almost and we can say that C-P is as strong as E-P propagation relationship.

Figure 35 - Phase Propagation Tornado Diagram

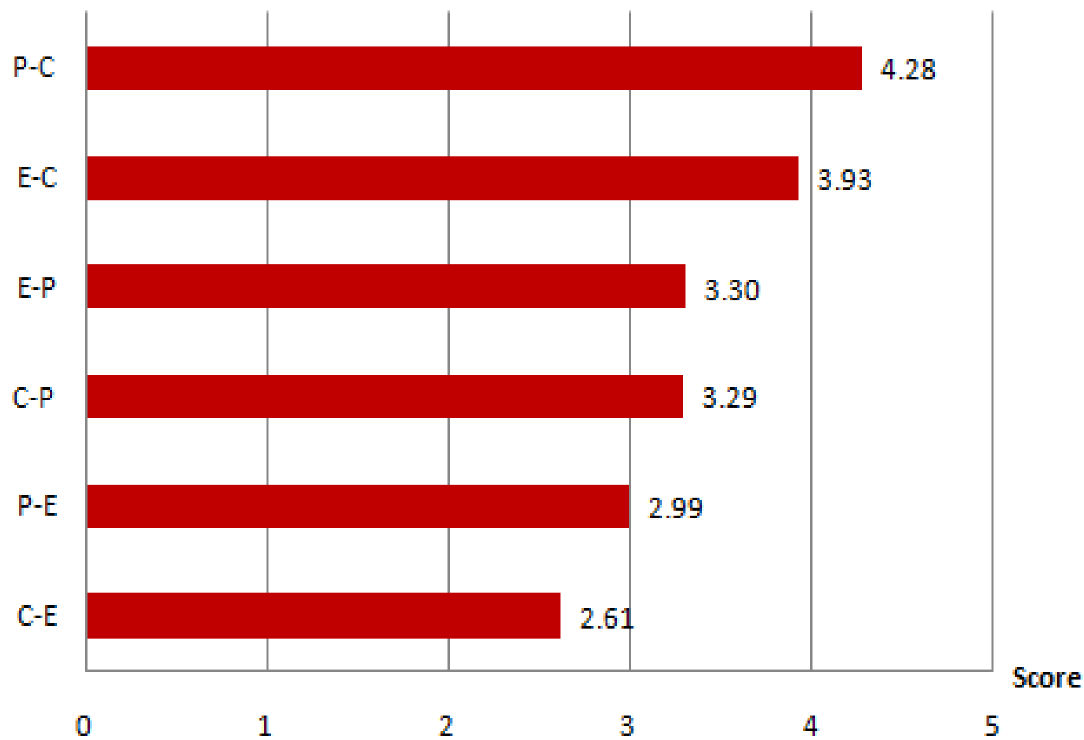
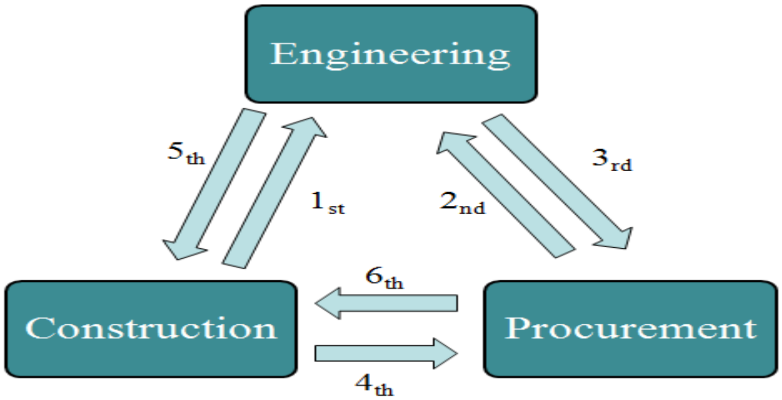


Figure 36 - Phase Propagation Triangular Diagram



4.2.Survey Two Analysis

Survey Two was developed to analyze the relationship among the risk events in engineering, procurement, and construction phases and project management areas (scope management, time management, cost management, quality management, resource management, communication management, and safety management). The participants were asked to answer the questions online via SurveyMonkey website, which is an online survey development cloud-based company.

4.2.1. Univariate Analysis

In the Survey Two, we invited many experts and practitioners who had good experience and education ability to answer our research questions of the survey. In this section, we explained background of 241 participants in Survey Two by using univariate analysis as follow:

Figure 37 shows the educational background of the 241 people who participated in Survey Two. As one can see, 86% have 4 or more years or college experience.

Figure 37 - Education Background of Participants

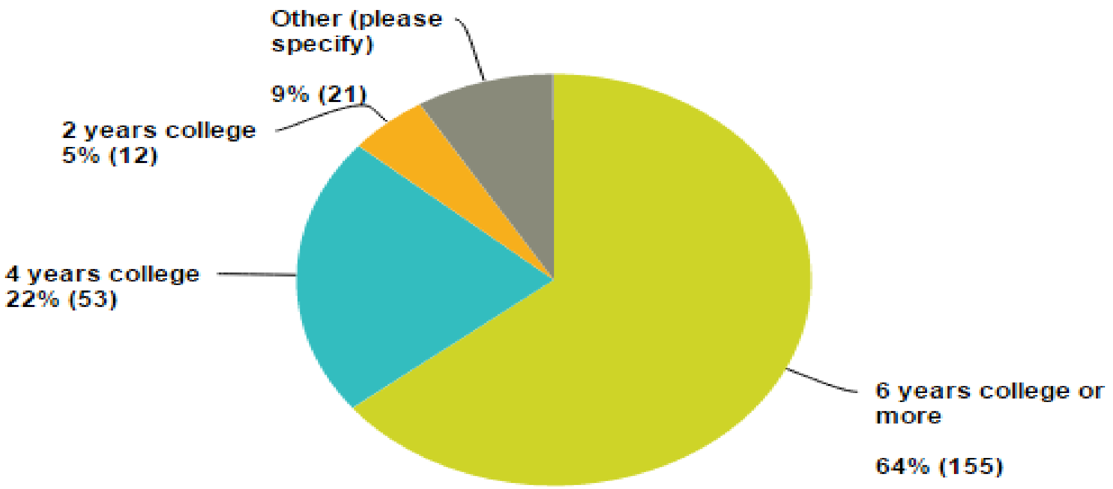


Figure 38 shows the project experience background of the 241 people who participated in Survey Two. The graph shows that more than 86% have a minimum of 5 years of experience on projects.

Figure 38 - Experience Background of Participants

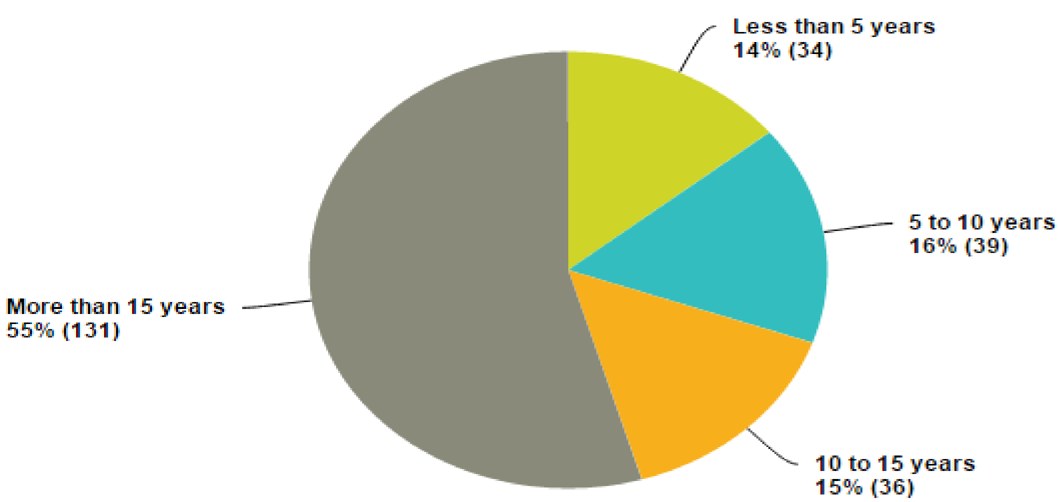


Figure 39 shows the typical role of the 241 people who participated in Survey Two. The graph shows that more than 45% hold the position of project manager.

Figure 39 - Background of Participants: Roles

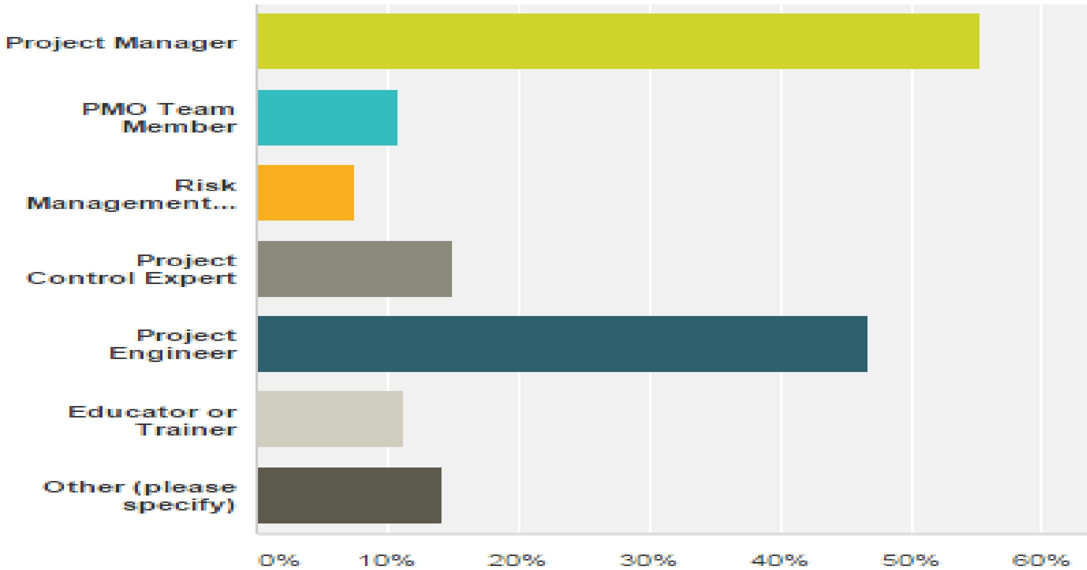
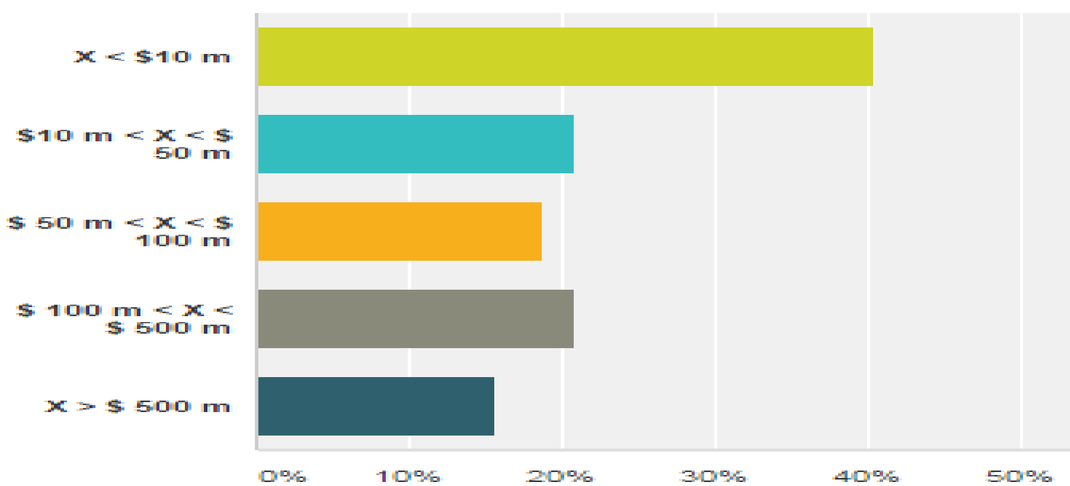


Figure 40 shows the average value the projects (millions of dollars) which participants work in based on Survey Two.

Figure 40- Background of Participants: Project Dollar Value in Millions



In Figure 41, we can see project type distributions according to Survey Two. Approximately 40% of participants have experience working on infrastructure projects, which are the most complicated type of construction projects.

Figure 41- Background of Participants: Project Type

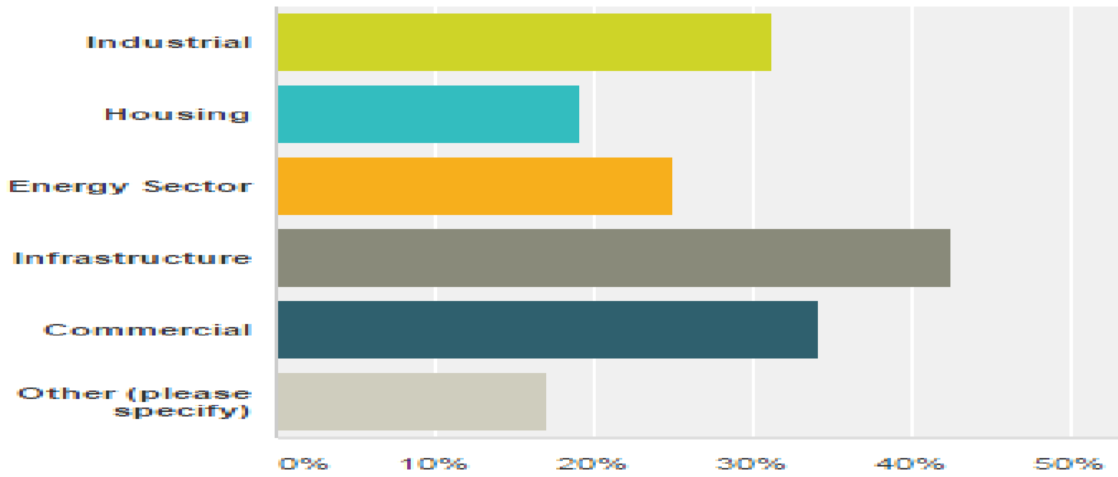
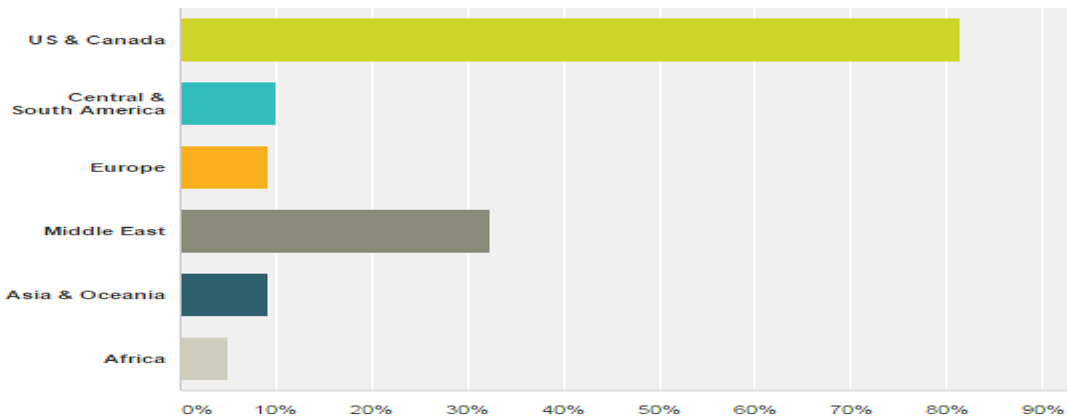


Figure 42 shows the project location distributions in the world based on respondents' to Survey Two. Approximately 30% of responders have experience in Middle Eastern countries, and more than 80% have experience in U.S. and Canadian projects.

Figure 42 - Global Scattering of Participants



In this study, twenty-eight models were created by using binary logistic regression analysis to represent the impact of risk events on each identified project knowledge base areas (scope management, time management, cost management, quality management, resources management, safety management, and communication management). Thus, twenty-eight different subsets were extracted from the main dataset. The extraction of cases was done as described in the following sections:

4.2.2. Time Management Models

4.2.2.1. Engineering Model in Time Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on time management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only six engineering risk events were significant, and the others (RE2, RE4, RE8, RE10, RE11, and RE12) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 6 and Table 7 summarize the results of this analysis.

Table 6 - Engineering Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step1 [a]	RE1T(1)	1.826	.879	4.314	1	.038	6.209	1.108	34.784
	RE3T(1)	2.857	1.144	6.237	1	.013	17.409	1.849	163.883
	RE5T(1)	1.954	.838	5.441	1	.020	7.057	1.366	36.451
	RE6T(1)	2.536	1.167	4.724	1	.030	12.626	1.283	124.241
	RE7T(1)	3.135	1.045	9.004	1	.003	22.987	2.966	178.134
	RE9T(1)	2.475	.948	6.815	1	.009	11.879	1.853	76.158
	Constant	-4.132	1.205	11.763	1	.001	.016		

a. -2 Loglikelihood = 43.034; Hosmer and Lemeshow Chi-square Test =4.54, p=0.85

Table 7 - Relative Importance of Variables in the Engineering Model

Variable	Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
RE1T	-23.905	4.775	1	.029
RE3T	-26.447	9.861	1	.002
RE5T	-24.566	6.098	1	.014
RE6T	-24.759	6.484	1	.011
RE7T	-28.450	13.866	1	.000
RE9T	-25.608	8.182	1	.004

One can see the developed model's loglikelihood value (43.034) in the Table 6 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.85 is greater than 0.05 and supports the goodness of fit for the model.

When we closely examined the process, the model at the first step was the best at predicting the degree of association in the time management area and engineering risk events. Its prediction power or accuracy was measured at 94.5%, which was greater than the naive predictor power (89%). (See Table 8)

Table 8 - The Engineering Model Classification Table

			Predicted		
			EDV		Percentage Correct
	Observed		NO	YES	
Step 1	EDV	NO	13	7	65.0
		YES	3	158	98.1
	Overall Percentage				94.5

Table 9 - Validation Set

Count

		Strong Affected		
		No	Yes	Total
DV	No	7	4	11
	Yes	2	47	49
Total		9	51	60

As previously mentioned the data was split in two to develop and validate the model. Table 9 shows the prediction power of the model as 94.5%. It was also found that the same model correctly predicted 90% of the validation data (See Table 9) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

Also, Table 6 lists the variables in the model used to predict the degree of association on time management for engineering risk events. In light of this information “Design errors and omissions” (RE1), Error to update technical and project documents (RE3), Late design decisions and drawings (RE5), Inadequate quality planning (RE6), Inadequate resource planning (RE7), and Inadequate time scheduling (RE9) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and time management area.

When we questioned which independent variable is critical for the engineering in the time management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 7 indicates, removing the “Inadequate resource planning” (RE7) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RE7 is the most important independent variable among the others in the model of the engineering phase in the time management.

4.2.2.2. Procurement Model in Time Management Area

It is generally believed that procurement and time management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on time management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2. This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only six procurement risk events were significant, and the others (RP4, RP5, RP6, and RP7) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 10 and Table 11 summarize the results of this analysis.

Table 10 - Procurement Model Results

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
[a] RP1T(1)	5.711	1.814	9.907	1	.002	302.261	8.627	10589.672
RP2T(1)	4.644	1.631	8.103	1	.004	103.929	4.248	2542.956
RP3T(1)	2.830	1.223	5.349	1	.021	16.940	1.540	186.353
RP8T(1)	5.314	1.710	9.663	1	.002	203.224	7.125	5796.824
RP9T(1)	3.260	1.290	6.388	1	.011	26.045	2.079	326.278
RP10T(1)	5.470	1.652	10.962	1	.001	237.429	9.316	6050.846
Constant	-5.944	1.702	12.196	1	.000	.003		

a. -2 Loglikelihood = 34.23; Hosmer and Lemeshow Chi-square Test = 2.83, p=0.94

Table 11 - Relative Importance of Variables in the Procurement Model

Variable	Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
RP1T	-26.789	19.347	1	.000
RP2T	-26.501	18.770	1	.000
RP3T	-21.060	7.889	1	.005
RP8T	-27.450	20.668	1	.000
RP9T	-22.153	10.075	1	.002
RP10T	-30.218	26.205	1	.000

One can see the developed model's loglikelihood value (34.23) in the Table 10 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.94 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association in the time management area and procurement risk events. Its prediction power or accuracy was measured at 95.6%, which was greater than the naive predictor power (85.6%). (See Table 12)

Table 12 - The procurement Model Classification Table

			Predicted		
			DV		Percentage
	Observed		No	Yes	Correct
Step 1	DV	No	23	3	88.5
		Yes	5	150	96.8
	Overall Percentage				95.6

Table 13 - Validation Set

Count

		DV		
		No	Yes	Total
DV	No	10	1	11
	Yes	0	49	49
Total		10	50	60

As previously mentioned the data was divided in two to develop and validate the model. Table 12 shows the prediction power of the model as 95.6%. It was also found that the same model correctly predicted 98.3% of the validation data (See Table 13) that

means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 10 lists the variables in the model to forecast the degree of association on time management and procurement risk events. In light of this information showed RP1, RP2, RP3, RP8, RP9, and RP10 (Table 10) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and time management area. the ß0 is negative which indicates that the lowering affect on the probabilities outcome.

When we questioned which independent variable is critical for the procurement in the time management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 11 indicates, removing the "Availability resources for subcontractors and vendors" (RP10) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be concluded that RP10 is the most important independent variable among the others in the model of the procurement phase in the time management.

4.2.2.3. Construction Model in Time management Area

Many people believe that the construction risk events and time management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with time management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only six construction risk events were significant, and the others (RC2, RC3, RC4, RC6, RC7, RC10, RC12, RC13, RC15, RC16, RC17, and RC18) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 14 and Table 15 summarize the results of this analysis.

Table 14 - Construction Model Result

								95% C.I.for EXP(B)	
		B	S.E.	Wald	Df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	RC1T(1)	4.145	1.302	10.134	1	.001	63.132	4.919	810.252
	RC5T(1)	3.517	1.465	5.764	1	.016	33.678	1.908	594.582
	RC8T(1)	4.260	1.739	6.000	1	.014	70.797	2.343	219.246
	RC9T(1)	6.577	2.243	8.594	1	.003	718.315	8.844	581.416
	RC11T(1)	3.635	1.336	7.398	1	.007	37.891	2.761	520.019
	RC14T(1)	3.969	1.432	7.683	1	.006	52.916	3.198	875.636
	Constant	-7.613	2.338	10.600	1	.001	.000		

a. -2 Loglikelihood = 32.85; Hosmer and Lemeshow Chi-square Test = 0.387, p=1.00

Table 15 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC1T	-26.009	19.833	1	.000
	RC5T	-20.354	8.523	1	.004
	RC8T	-21.117	10.050	1	.002
	RC9T	-28.993	25.801	1	.000
	RC11T	-22.500	12.814	1	.000
	RC14T	-22.781	13.378	1	.000

As we can see the developed model's loglikelihood value (32.85) in the Table 14 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.94 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association in the time management area and construction risk events. Its prediction power or accuracy was measured at 95.6%, which was greater than the naive predictor power (82.9%). (See Table 16)

Table 16 - The Construction Model Classification Table

	Observed		Predicted: DV No	Predicted: DV Yes	Predicted: Percentage Correct
Step 1	DV	No	25	6	80.6
		Yes	2	148	98.7
	Overall Percentage				95.6

Table 17 - Validation Set

Count

		Strongly Affected		Total
		No	Yes	
DV	No	12	1	13
	Yes	4	43	47
Total		16	44	60

As previously mentioned the data was divided in two to develop and validate the model. Table 16 shows the prediction power of the model as 95.6%. It was also found that the same model correctly predicted 91.7% of the validation data (See Table 17)) and there is not too much difference between the model and validation and we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 14 lists the variables in the model to forecast the degree of association on time management and construction risk events. In light of this information showed RC1, RC5, RC8, RC9, RC11 and RC14 (Table 14) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and time management area.

When we questioned which independent variable is critical for the construction in the time management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 15 indicates, removing the “Inadequate resource management” (RC9) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RC9 is the most important independent variable among the others in the model of the construction phase in the time management.

4.2.2.4. Top 8 Risk Events Model in Time Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, 2, and 3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with time management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only five risk events were significant, and the others (RE5, RE12, and RC7) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 18 and Table 19 summarize the results of this analysis.

Table 18 - The Top 8 Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE8T(1)	1.426	.664	4.614	1	.032	4.161	1.133	15.285
	RP4T(1)	2.001	.739	7.340	1	.007	7.398	1.739	31.471
	RP8T(1)	1.415	.608	5.406	1	.020	4.115	1.249	13.562
	RP10T(1)	2.284	.694	10.819	1	.001	9.811	2.516	38.252
	RC5T(1)	1.428	.603	5.605	1	.018	4.172	1.279	13.609
	Constant	-1.573	.597	6.946	1	.008	.207		

a. -2 Loglikelihood = 88.718; Hosmer and Lemeshow Chi-square Test = 15.507, p=0.05

Table 19 - Relative Importance of Variables in the Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RE8T	-47.029	5.339	1	.021
	RP4T	-49.171	9.625	1	.002
	RP8T	-47.392	6.066	1	.014
	RP10T	-51.537	14.357	1	.000
	RC5T	-47.239	5.760	1	.016

One can see the developed model's loglikelihood value (88.718) in the Table 18 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.05 is equal supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association in the time management area and top eight risk events. Its prediction power or accuracy was measured at 89.5%, which was greater than the naive predictor power (85.1%). (See Table 20)

Table 20 - The Top 8 Model Classification Table

	Observed		Predicted: Strongly affected No	Predicted: Strongly affected Yes	Predicted: Percentage Correct
Step 1	DV	No	17	10	63.0
		Yes	9	145	94.2
	Overall Percentage				89.5

Table 21 - Validation Set

Count

		Strongly Affected No	Strongly Affected Yes	Total
DV	No	5	5	10
	Yes	4	46	50
Total		9	51	60

As previously mentioned the data was divided in two to develop and validate the model. Table 20 shows the prediction power of the model as 89.5%. It was also found that the same model correctly predicted 85% of the validation data (See Table 21) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 18 lists the variables in the model to forecast the degree of association on time management and construction risk events. In light of this information showed RE8, RP4, RP8, RP10, and RC5 (Table 18) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and time management area.

When we questioned which independent variable is critical for the top 8 risk events in the time management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 19 indicates, removing the “Availability resources for subcontractors and vendors” (RP10) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be concluded that RP10 is the most important independent variable among the others in the model of the top 8 risk events in the time management.

4.2.3. Scope Management Models

4.2.3.1. Engineering Model in Scope Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on scope management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the “stepwise backward LR” method. First, it was revealed that only six engineering risk events were significant, and the others (RE1, RE5, RE6, RE7, and RE12) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 22 and Table 23 summarize the results of this analysis.

Table 22 - The Engineering Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE2Sco(1)	1.811	.662	7.473	1	.006	6.115	1.669	22.402
	RE3Sco(1)	3.441	.835	16.989	1	.000	31.216	6.078	160.317
	RE4Sco(1)	3.586	.869	17.044	1	.000	36.086	6.577	198.004
	RE8Sco(1)	3.086	.766	16.225	1	.000	21.896	4.877	98.302
	RE9Sco(1)	3.654	.913	16.024	1	.000	38.614	6.454	231.027
	RE10Sco(1)	2.719	.787	11.946	1	.001	15.160	3.245	70.832
	RE11Sco(1)	3.276	.788	17.280	1	.000	26.459	5.647	123.965
	Constant	-6.405	1.289	24.706	1	.000	.002		

a. -2 Loglikelihood = 84.34; Hosmer and Lemeshow Chi-square Test =7.83, p=0.45

Table 23 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE2Sco	-46.572	8.805	1	.003
	RE3Sco	-55.948	27.557	1	.000
	RE4Sco	-56.218	28.097	1	.000
	RE8Sco	-54.052	23.764	1	.000
	RE9Sco	-54.705	25.070	1	.000
	RE10Sco	-49.229	14.119	1	.000
	RE11Sco	-55.836	27.332	1	.000

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the scope management area and engineering risk events. Its prediction power or accuracy was measured at 91.2%, which was greater than the naive predictor power (71.3%). (See Table 24)

Table 24 - The Engineering Model Classification Table

			Predicted		
			DV		Percentage Correct
	Observed		No	Yes	
Step 1	DV	No	48	4	92.3
		Yes	12	117	90.7
	Overall Percentage				91.2

a. The cut value is .500

Table 25 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	19	1	20
	Yes	2	38	40
Total		21	39	60

One can see the developed model's loglikelihood value (84.32) in the Table 22 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.45 is greater than 0.05 and supports the goodness of fit for the model.

As previously mentioned the data was split in two to develop and validate the model. Table 25 shows the prediction power of the model as 91.2%. It was also found that the same model correctly predicted 95% of the validation data (See Table 25) which

means the model more accurately predicts the degree of association than the naive prediction.

Also, Table 22 lists the variables in the model used to predict the degree of association on scope management for engineering risk events. In light of this information, RE2, RE3, RE4, RE8, RE9, RE10, and RE11 (See Table 2 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and scope management area.

When we questioned which independent variable is critical for the engineering in the scope management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 23 indicates, removing the "Errors and omissions in shop drawings" (RE4) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RE4 is the most important independent variable among the others in the model of the engineering phase in the scope management.

4.2.3.2. Procurement Model in Scope Management Area

It is generally believed that procurement and scope management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on scope management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as presented in Table 2.

This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only six procurement risk events were significant, and the others (RP4, RP6, RP9, and RP10) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 26 and Table 27 summarize the results of this analysis.

Table 26 - The Procurement Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RP1Sco(1)	4.376	.857	26.097	1	.000	79.507	14.835	426.110
	RP2Sco(1)	3.558	1.009	12.424	1	.000	35.081	4.852	253.643
	RP3Sco(1)	2.927	.723	16.415	1	.000	18.677	4.532	76.970
	RP5Sco(1)	7.260	1.585	20.982	1	.000	1422.772	63.674	31791.479
	RP7Sco(1)	3.898	.806	23.407	1	.000	49.325	10.167	239.300
	RP8Sco(1)	3.189	.724	19.382	1	.000	24.252	5.865	100.285
	Constant	-7.587	1.361	31.095	1	.000	.001		

a. -2 Loglikelihood = 91.073; Hosmer and Lemeshow Chi-square Test = 3.52, p=0.9

Table 27 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RP1Sco	-71.917	52.761	1	.000
	RP2Sco	-54.664	18.255	1	.000
	RP3Sco	-58.020	24.968	1	.000
	RP5Sco	-67.973	44.872	1	.000
	RP7Sco	-67.589	44.106	1	.000
	RP8Sco	-60.976	30.879	1	.000

As we can see the developed model's loglikelihood value (91.073) in the Table 26 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.90 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the scope management area and procurement risk events. Its prediction power or accuracy was measured at 87.8%, which was greater than the naive predictor power (54.1%). (See Table 28)

Table 28 - The Procurement Model Classification Table

			Predicted		
			DV		Percentage Correct
	Observed		No	Yes	
Step 1	DV	No	78	5	94.0
		Yes	17	81	82.7
	Overall Percentage				87.8

a. The cut value is .500

Table 29 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	23	5	28
	Yes	7	25	32
Total		30	30	60

As previously mentioned the data was divided in two to develop and validate the model. Table 28 shows the prediction power of the model as 87.8%. It was also found that the same model correctly predicted 80% of the validation data (See Table 29) that means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 26 lists the variables in the model to forecast the degree of association on scope management and procurement risk events. In light of this information showed RP1, RP2, RP3, RP5, RP7, and RP8 (Table 26) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and scope management area.

When we questioned which independent variable is critical for the procurement in the scope management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 27 indicates, removing the “Errors in bidding process” (RP1) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RP1 is the most important independent variable among the others in the model of the procurement phase in the scope management.

4.2.3.3. Construction Model in Scope Management Area

Many people believe that the construction risk events and scope management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with scope management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only six construction risk events were significant, and the others (RC7, RC11, RC12, RC15, RC16, RC17, and RC18) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 30 and Table 31 summarize the results of this analysis.

Table 30 - The Construction Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC1Sco(1)	1.938	.703	7.608	1	.006	6.947	1.752	27.543
	RC2Sco(1)	2.050	.685	8.963	1	.003	7.767	2.030	29.724
	RC3Sco(1)	1.813	.727	6.215	1	.013	6.130	1.474	25.498
	RC4Sco(1)	2.201	.980	5.040	1	.025	9.032	1.322	61.690
	RC5Sco(1)	3.177	.812	15.323	1	.000	23.984	4.886	117.718
	RC6Sco(1)	2.427	.755	10.323	1	.001	11.320	2.576	49.743
	RC8Sco(1)	1.704	.669	6.489	1	.011	5.498	1.481	20.402
	RC9Sco(1)	2.300	.815	7.961	1	.005	9.978	2.019	49.318
	RC10Sco(1)	1.858	.821	5.118	1	.024	6.411	1.282	32.067
	RC13Sco(1)	2.240	.738	9.199	1	.002	9.392	2.209	39.933
	RC14Sco(1)	2.934	.787	13.912	1	.000	18.803	4.024	87.862
	Constant	-10.151	1.865	29.615	1	.000	.000		

a. . -2 Loglikelihood = 71.689; Hosmer and Lemeshow Chi-square Test = 2.739, p=0.95

Table 31 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC1Sco	-40.285	8.882	1	.003
	RC2Sco	-41.246	10.803	1	.001
	RC3Sco	-39.383	7.078	1	.008
	RC4Sco	-38.825	5.961	1	.015
	RC5Sco	-46.593	21.496	1	.000
	RC6Sco	-42.022	12.355	1	.000
	RC8Sco	-39.471	7.253	1	.007
	RC9Sco	-40.516	9.344	1	.002
	RC10Sco	-38.675	5.660	1	.017
	RC13Sco	-41.352	11.014	1	.001
	RC14Sco	-45.186	18.683	1	.000

As we can see the developed model's loglikelihood value (71.689) in the Table 30 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.95 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the scope management area and construction risk events. Its prediction power or accuracy was measured at 90.1%, which was greater than the naive predictor power (63.5%). (See Table 32)

Table 32 - The Construction Model Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			NO	YES	
Step 1	CDV	NO	105	10	91.3
		YES	8	58	87.9
	Overall Percentage				90.1

Table 33 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	36	1	37
	Yes	10	13	23
Total		46	14	60

As previously mentioned the data was divided in two to develop and validate the model. Table 16 shows the prediction power of the model as 90.1%. It was also found that the same model correctly predicted 81.7% of the validation data (See Table 33) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 30 lists the variables in the model to forecast the degree of association on scope management and construction risk events. In light of this information showed RC1, RC2, RC3, RC4, RC5, RC6, RC8, RC9, RC10, RC13 and RC14 (Table 30) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and scope management area.

When we questioned which independent variable is critical for the construction in the scope management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 31 indicates, removing the “Delay in decision making and approval” (RC5) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RC5 is the most important independent variable among the others in the model of the construction phase in the scope management.

4.2.3.4. Top 8 Risk Events Model in Scope Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, 2, and 3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with scope management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only six risk events were significant, and the others (RP4 and RC7) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 34 and Table 35 summarize the results of this analysis.

Table 34 - The Top 8 Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE5Sco	1.133	.419	7.329	1	.007	3.105	1.367	7.053
	RE8Sco	1.516	.399	14.436	1	.000	4.553	2.083	9.952
	RE12Sco	.983	.404	5.920	1	.015	2.673	1.211	5.900
	RP8Sco	1.387	.408	11.561	1	.001	4.002	1.799	8.902
	RP10Sco	2.286	.877	6.802	1	.009	9.839	1.765	54.853
	RC5Sco	1.786	.522	11.692	1	.001	5.964	2.143	16.601
	Constant	-2.546	.429	35.293	1	.000	.078		

a. -2 Loglikelihood = 163.3; Hosmer and Lemeshow Chi-square Test = 3.22, p=0.86

Table 35 - Relative Importance of Variables in the Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE5Sco	-85.469	7.630	1	.006
	RE8Sco	-89.372	15.437	1	.000
	RE12Sco	-84.709	6.112	1	.013
	RP8Sco	-87.837	12.368	1	.000
	RP10Sco	-86.247	9.187	1	.002
	RC5Sco	-88.238	13.170	1	.000

One can see the developed model's loglikelihood value (163.3) in the Table 34 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.86 is greater than 0.05 and supports the goodness of fit for the model.

Table 36 - The Top 8 Model Classification Table

			Predicted		
			DV		Percentage Correct
	Observed		No	Yes	
Step 1	DV	No	76	14	84.4
		Yes	22	69	75.8
	Overall Percentage				80.1

Table 37 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	25	5	30
	Yes	5	25	30
Total		30	30	60

After the process was examined, the model at the first step showed the best at predicting the degree of association among the scope management area and top eight risk events. Its prediction power or accuracy was measured at 80.1%, which was greater than the naive predictor power (50.3%). (See Table 36)

As previously mentioned the data was divided in two to develop and validate the model. Table 36 shows the prediction power of the model as 80.1%. It was also found that the same model correctly predicted 83% of the validation data (See Table 37) which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 34 lists the variables in the model to forecast the degree of association on scope management and construction risk events. In light of this information showed RE5, RE8, RE12, RP8, RP10, and RC5 (Table 34) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and scope management area.

When we questioned which independent variable is critical for the top 8 risk events in the scope management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 35 indicates, removing the “Inadequate change management process” (RP8) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RP8 is the most important independent variable among the others in the model of the top 8 risk events in the scope management.

4.2.4. Quality Management Models

4.2.4.1. Engineering Model in Quality Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on quality management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the “stepwise backward LR” method. First, it was revealed that only six engineering risk events were significant, and the others (RE1, RE8, RE9, RE10, and RE11) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 38 and Table 39 summarize the results of this analysis.

Table 38 - The Engineering Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE2Q(1)	3.114	.984	10.025	1	.002	22.511	3.275	154.732
	RE3Q(1)	2.480	.931	7.100	1	.008	11.943	1.927	74.031
	RE4Q(1)	1.650	.820	4.046	1	.044	5.204	1.043	25.968
	RE5Q(1)	4.243	1.341	10.015	1	.002	69.632	5.029	964.142
	RE6Q(1)	2.403	.939	6.555	1	.010	11.061	1.757	69.642
	RE7Q(1)	2.706	1.171	5.344	1	.021	14.972	1.510	148.488
	RE12Q(1)	3.650	1.082	11.384	1	.001	38.493	4.618	320.883
	Constant	-5.278	1.412	13.969	1	.000	.005		

a. -2 Loglikelihood = 46.827; Hosmer and Lemeshow Chi-square Test =1.343, p=0.987

Table 39 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE2Q	-31.078	15.330	1	.000
	RE3Q	-27.965	9.103	1	.003
	RE4Q	-25.720	4.613	1	.032
	RE5Q	-32.507	18.187	1	.000
	RE6Q	-27.676	8.525	1	.004
	RE7Q	-27.361	7.896	1	.005
	RE12Q	-32.619	18.411	1	.000

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the quality management area and engineering risk events. Its prediction power or accuracy was measured at 95.6%, which was greater than the naive predictor power (83.4%). (See Table 40)

Table 40 - The Engineering Model Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	24	6	80.0
		Yes	2	149	98.7
	Overall Percentage				95.6

Table 41 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	2	2	4
	Yes	2	54	56
Total		4	56	60

One can see the developed model's loglikelihood value (46.827) in the Table 38 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.98 is greater than 0.05 and supports the goodness of fit for the model.

As previously mentioned the data was split in two to develop and validate the model. Table 40 shows the prediction power of the model as 95.6%. It was also found that the same model correctly predicted 93.3% of the validation data (See Table 41) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

Also, Table 38 lists the variables in the model used to predict the degree of association on quality management for engineering risk events. In light of this information, RE2, RE3, RE4, RE5, RE6, RE7, and RE12 (See Table 2 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and quality management area.

When we questioned which independent variable is critical for the engineering in the quality management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 39 indicates, removing the “Using lesson learned in design” (RE12) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RE12 is the most important independent variable among the others in the model of the engineering phase in the quality management.

4.2.4.2. Procurement Model in Quality Management Area

It is generally believed that procurement and quality management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on quality management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2. This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only eight procurement risk events were significant, and the others (RP7 and RP9) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 42 and Table 43 summarize the results of this analysis.

Table 42 - The Procurement Model Results

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	RP1Q(1)	6.541	2.141	9.335	1	.002	692.966	10.434	46024.843
	RP2Q(1)	5.766	1.948	8.764	1	.003	319.117	7.018	14511.013
	RP3Q(1)	7.551	2.107	12.843	1	.000	1903.213	30.613	118322.676
	RP4Q(1)	3.126	1.479	4.466	1	.035	22.773	1.254	413.457
	RP5Q(1)	4.002	1.474	7.375	1	.007	54.714	3.046	982.872
	RP6Q(1)	5.162	1.766	8.543	1	.003	174.571	5.477	5563.937
	RP8Q(1)	8.270	2.396	11.912	1	.001	3904.094	35.643	427631.309
	RP10Q(1)	5.525	1.814	9.275	1	.002	250.794	7.165	8778.093
	Constant	-12.117	3.529	11.790	1	.001	.000		

a. -2 Loglikelihood = 39.088; Hosmer and Lemeshow Chi-square Test = 22.919, p= 0.003.

Table 43 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RP1Q	-32.124	25.159	1	.000
	RP2Q	-30.063	21.038	1	.000
	RP3Q	-38.967	38.845	1	.000
	RP4Q	-23.227	7.366	1	.007
	RP5Q	-26.089	13.090	1	.000
	RP6Q	-28.534	17.980	1	.000
	RP8Q	-44.127	49.165	1	.000
	RP10Q	-32.758	26.428	1	.000

As we can see the developed model's loglikelihood value (39.088) in the Table 42 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than .05; hence, the significance value of 0.03 is smaller than 0.05 and supports the weakness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the quality management area and procurement risk events. Its prediction power or accuracy was measured at 95.6%, which was greater than the naive predictor power (72.9%). (See Table 44)

Table 44 - The Procurement Model Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	45	4	91.8
		Yes	4	128	97.0
	Overall Percentage				95.6

Table 45 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	16	4	20
	Yes	0	40	40
Total		16	44	60

As previously mentioned the data was divided in two to develop and validate the model. Table 44 shows the prediction power of the model as 95.6%. It was also found that the same model correctly predicted 93.3% of the validation data (See Table 45) and there is not too much difference between the model and validation. Thus, we can ignore the gap that means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 42 lists the variables in the model to forecast the degree of association on quality management and procurement risk events. In light of this information showed RP1, RP2, RP3, RP4, RP5, RP6, RP8, RP10 (Table 42) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and quality management area.

When we questioned which independent variable is critical for the procurement in the quality management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 43 indicates, removing the “Inadequate change management process” (RP8) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RP8 is the most important independent variable among the others in the model of the procurement phase in the quality management.

4.2.4.3. Construction Model in Quality Management Area

Many people believe that the construction risk events and quality management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with quality management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the first effort, it was revealed that only seven construction risk events were significant, and the others (RC1, RC2, RC3, RC4, RC5, RC6, RC7, RC8, RC12, RC15, RC17, and RC18) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 46 and Table 47 summarize the results of this analysis.

Table 46 - The Construction Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC2Q(1)	2.264	.629	12.961	1	.000	9.622	2.805	33.006
	RC9Q(1)	1.307	.572	5.224	1	.022	3.694	1.205	11.327
	RC10Q(1)	1.199	.508	5.583	1	.018	3.317	1.227	8.970
	RC11Q(1)	1.834	.595	9.517	1	.002	6.260	1.952	20.073
	RC13Q(1)	1.893	.719	6.938	1	.008	6.639	1.623	27.154
	RC14Q(1)	1.826	.540	11.443	1	.001	6.208	2.155	17.881
	RC16Q(1)	2.008	.602	11.131	1	.001	7.448	2.290	24.229
	Constant	-3.387	.691	24.053	1	.000	.034		

a. -2 Loglikelihood = 103.424 ; Hosmer and Lemeshow Chi-square Test = 0.829 p=0.999

Table 47 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RC2Q	-59.810	16.197	1	.000
	RC9Q	-54.562	5.699	1	.017
	RC10Q	-54.561	5.699	1	.017
	RC11Q	-57.486	11.548	1	.001
	RC13Q	-55.915	8.406	1	.004
	RC14Q	-58.171	12.918	1	.000
	RC16Q	-58.501	13.579	1	.000

As we can see the developed model's loglikelihood value (103.424) in the Table 46 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.99 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the quality management area and construction risk events. Its prediction power or accuracy was measured at 85.1%, which was greater than the naive predictor power (71.3%). (See Table 48)

Table 48 - The Construction Model Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	38	14	73.1
		Yes	13	116	89.9
	Overall Percentage				85.1

Table 49 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	12	1	13
	Yes	11	36	47
Total		23	37	60

As previously mentioned the data was divided in two to develop and validate the model. Table 16 shows the prediction power of the model as 85.1%. It was also found that the same model correctly predicted 80% of the validation data (See Table 49) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 46 lists the variables in the model to forecast the degree of association on quality management and construction risk events. In light of this information showed RC2, RC9, RC10, RC11, RC13, RC14, RC16 and RC14 (Table 46) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and quality management area.

When we questioned which independent variable is critical for the construction in the quality management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 47 indicates, removing the “Scope and responsibility gaps between the prime (contractor) and subcontractors” (RC2) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RC2 is the most important independent variable among the others in the model of the construction phase in the quality management.

4.2.4.4. Top 8 Risk Events Model in Quality Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, 2, and 3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with quality management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the first effort, it was revealed that only five risk events were significant, and the others

(RP4, RP8, and RP5) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 50 and Table 51 summarize the results of this analysis.

Table 50 - The Top 8 Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE5Q(1)	1.214	.525	5.340	1	.021	3.367	1.202	9.426
	RE8Q(1)	1.185	.594	3.978	1	.046	3.272	1.021	10.488
	RE12Q(1)	1.932	.530	13.301	1	.000	6.904	2.444	19.502
	RP10Q(1)	1.562	.538	8.443	1	.004	4.770	1.663	13.681
	RC7Q(1)	2.190	.579	14.306	1	.000	8.938	2.873	27.807
	Constant	-1.650	.455	13.172	1	.000	.192		

a. -2 Loglikelihood = 112.46; Hosmer and Lemeshow Chi-square Test = 4.32, p=0.829

Table 51 - Relative Importance of Variables in the Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RE5Q	-59.076	5.725	1	.017
	RE8Q	-58.384	4.343	1	.037
	RE12Q	-64.024	15.622	1	.000
	RP10Q	-60.988	9.550	1	.002
	RC7Q	-65.377	18.327	1	.000

One can see the developed model's loglikelihood value (112.46) in the Table 50 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.829 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the quality management area and top eight risk events. Its prediction power or accuracy was measured at 86.7%, which was greater than the naive predictor power (77.9%). (See Table 52)

Table 52 - The Top 8 Model Classification Table

			Predicted		
			DV		Percentage
	Observed		No	Yes	Correct
Step 1	DV	No	25	15	62.5
		Yes	9	132	93.6
	Overall Percentage				86.7

Table 53 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	3	8	11
	Yes	3	46	49
Total		6	54	60

As previously mentioned the data was divided in two to develop and validate the model. Table 36 shows the prediction power of the model as 86.7%. It was also found that the same model correctly predicted 85% of the validation data (See Table 53) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 50 lists the variables in the model to forecast the degree of association on quality management and construction risk events. In light of this information showed RE5, RE8, RE12, RP10, RC7 (Table 50) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and quality management area.

When we questioned which independent variable is critical for the top 8 risk events in the quality management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 51 indicates, removing the “Delay in decision making and approval” (RC5) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RC5 is the most important independent variable among the others in the model of the top 8 risk events in the quality management.

4.2.5. Resource Management Models

4.2.5.1. Engineering Model in Resource Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on resource management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only five engineering risk events were significant, and the others (RE1, RE2, RE3, RE6, RE10, and RE11) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 54 and Table 55 summarize the results of this analysis.

Table 54 - The Engineering Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE7Res(1)	1.322	.557	5.622	1	.018	3.750	1.258	11.183
	RE8Res(1)	1.964	.546	12.931	1	.000	7.128	2.444	20.791
	RE9Res(1)	1.305	.549	5.658	1	.017	3.688	1.258	10.809
	RE5Res(1)	2.901	.695	17.443	1	.000	18.187	4.662	70.947
	RE4Res(1)	2.802	.732	14.636	1	.000	16.479	3.922	69.248
	RE12Res(1)	2.490	.586	18.067	1	.000	12.066	3.827	38.043
	Constant	-3.557	.689	26.621	1	.000	.029		

a. -2 Loglikelihood = 99.301; Hosmer and Lemeshow Chi-square Test = 6.22, p=0.623

Table 55 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RE7Res	-52.652	6.004	1	.014
	RE8Res	-57.104	14.908	1	.000
	RE9Res	-52.663	6.026	1	.014
	RE5Res	-62.204	25.107	1	.000
	RE4Res	-60.046	20.791	1	.000
	RE12Res	-61.168	23.035	1	.000

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the resource management area and engineering risk events. Its prediction power or accuracy was measured at 86.7%, which was greater than the naive predictor power (68%). (See Table 56)

Table 56 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	44	14	75.9
		Yes	10	113	91.9
	Overall Percentage				86.7

Table 57 - Validation Set

			DV		Total
			NO	YES	
DV	NO	Count	16	8	24
			66.7%	33.3%	100.0%
	YES	Count	5	31	36
			13.9%	86.1%	100.0%
Total		Count	21	39	60
			35.0%	65.0%	100.0%

As previously mentioned the data was split in two to develop and validate the model. Table 56 shows the prediction power of the model as 86.7%. It was also found that the same model correctly predicted 78.3% of the validation data (See Table 57) which means the model less accurately predicts the degree of association than the naive prediction.

One can see the developed model's loglikelihood value (99.3) in the Table 54 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.623 is greater than 0.05 and supports the goodness of fit for the model.

Also, Table 54 lists the variables in the model used to predict the degree of association on resource management for engineering risk events. In light of this information, RE7, RE8, RE9, RE5, RE4, RE12 (See Table 2 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and resource management area.

When we questioned which independent variable is critical for the engineering phase in the resource management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 55 indicates, removing the "Late design decisions and drawings" (RE5) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RE5 is the most important independent variable among the others in the model of the engineering in the resource management.

4.2.5.2. Procurement Model in Resource Management Area

It is generally believed that procurement and resource management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on resource management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2. This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only seven procurement risk events were significant, and the others (RP4, RP5, and RP7) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 58 and Table 59 summarize the results of this analysis.

Table 58 - The Procurement Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	RP1Res(1)	5.400	1.645	10.772	1	.001	221.448	8.805	5569.243
	RP2Res(1)	3.138	1.198	6.855	1	.009	23.049	2.201	241.394
	RP3Res(1)	3.820	1.224	9.739	1	.002	45.596	4.141	502.091
	RP6Res(1)	5.115	1.299	15.498	1	.000	166.503	13.045	2125.180
	RP8Res(1)	4.323	1.319	10.749	1	.001	75.445	5.690	1000.254
	RP9Res(1)	6.429	1.638	15.411	1	.000	619.604	25.008	15351.274
	RP10Res(1)	6.289	1.533	16.829	1	.000	538.748	26.695	10872.921
	Constant	-10.212	2.501	16.667	1	.000	.000		

a. -2 Loglikelihood = 47.9; Hosmer and Lemeshow Chi-square Test =3.516, p= 0.898.

As we can see the developed model's loglikelihood value (47.9) in the Table 58 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.898 is greater than 0.05 and supports the wellness of fit for the model.

Table 59 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RP1Res	-36.552	25.205	1	.000
	RP2Res	-29.480	11.061	1	.001
	RP3Res	-32.873	17.848	1	.000
	RP6Res	-42.717	37.534	1	.000
	RP8Res	-34.873	21.846	1	.000
	RP9Res	-45.180	42.461	1	.000
	RP10Res	-48.260	48.620	1	.000

After the process was examined, the model at the first step showed the best at predicting the degree of association among the resource management area and procurement risk events. Its prediction power or accuracy was measured at 94.5%, which was greater than the naive predictor power (69.6%). (See Table 44)

Table 60 - Classification Table

	Observed		Predicted DV No	Predicted DV Yes	Percentage Correct
Step 1	DV	No	49	6	89.1
		Yes	4	122	96.8
	Overall Percentage				94.5

Table 61 - Validation Set

Count

		DV No	DV Yes	Total
DV	No	18	4	22
	Yes	6	32	38
Total		24	36	60

As previously mentioned the data was divided in two to develop and validate the model. Table 60 shows the prediction power of the model as 94.5%. It was also found that the same model correctly predicted 83.3% of the validation data (See Table 61) that means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 58 lists the variables in the model to forecast the degree of association on resource management and procurement risk events. In light of this information showed RP1, RP2, RP3, RP6, RP8, RP9, and RP10 (Table 58) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and resource management area.

When we questioned which independent variable is critical for the procurement phase in the resource management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 59 indicates, removing the "Availability resources for subcontractors" (RP10) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be concluded that RP10 is the most important independent variable among the others in the model of the procurement in the resource management.

4.2.5.3. Construction Model in Resource Management Area

Many people believe that the construction risk events and resource management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with resource management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only eight construction risk events were significant, and the others (RC1, RC2, RC3, RC4, RC6, RC9, RC10, RC13, RC14, RC15, and RC17) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 62 and Table 63 summarize the results of this analysis.

Table 62 - The Construction Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC2Res(1)	3.038	.811	14.034	1	.000	20.871	4.258	102.311
	RC5Res(1)	1.878	.811	5.370	1	.020	6.543	1.336	32.042
	RC7Res(1)	2.617	.871	9.029	1	.003	13.692	2.484	75.468
	RC8Res(1)	4.630	1.199	14.921	1	.000	102.487	9.783	1073.688
	RC11Res(1)	2.224	.797	7.789	1	.005	9.241	1.939	44.050
	RC12Res(1)	2.835	.800	12.544	1	.000	17.023	3.547	81.712
	RC16Res(1)	4.582	1.248	13.479	1	.000	97.737	8.466	1128.404
	RC18Res(1)	3.606	.942	14.645	1	.000	36.834	5.809	233.567
	Constant	-6.728	1.416	22.588	1	.000	.001		

a. -2 Loglikelihood = 62.4; Hosmer and Lemeshow Chi-square Test = 2.552, p=0.959.

Table 63 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC2Res	-41.384	20.365	1	.000
	RC5Res	-34.318	6.233	1	.013
	RC7Res	-47.195	11.986	1	.001
	RC8Res	-44.341	26.279	1	.000
	RC11Res	-36.051	9.699	1	.002
	RC12Res	-39.880	17.355	1	.000
	RC16Res	-44.374	26.345	1	.000
	RC18Res	-43.002	23.601	1	.000

As we can see the developed model's loglikelihood value (62.4) in the Table 62 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.959 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the resource management area and construction risk events. Its prediction power or accuracy was measured at 93.9%, which was greater than the naive predictor power (68.5%). (See Table 64)

Table 64 - Classification Table

	Observed		Predicted		
			CDV		Percentage Correct
			No	Yes	
Step 1	DV	No	50	7	87.7
		Yes	4	120	96.8
	Overall Percentage				93.9

Table 65 - Validation Set

			DV		
			No	Yes	Total
DV	No	Count	16	6	22
			72.7%	27.3%	100.0%
	Yes	Count	4	34	38
			10.5%	89.5%	100.0%
Total		Count	20	40	60
			33.3%	66.7%	100.0%

As previously mentioned the data was divided in two to develop and validate the model. Table 64 shows the prediction power of the model as 93.9%. It was also found that the same model correctly predicted 83.3% of the validation data (See Table 65) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 62 lists the variables in the model to forecast the degree of association on resource management and construction risk events. In light of this information showed RC2, RC5, RC7, RC8, RC11, RC12, RC16, RC18 a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and resource management area.

When we questioned which independent variable is critical for the construction phase in the resource management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 63 indicates, removing the “Fast tracking or crashing for accelerating time schedule”

(RC7) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be concluded that RC7 is the most important independent variable among the others in the model of the construction in the resource management.

4.2.5.4. Top 8 Risk Events Model in Resource Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, Table2, and Table3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with resource management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the second effort, it was revealed that only seven risk events were significant, and the RE8 was found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at $p=0.05$ significance level to create the model. Table 66 and Table 67 summarize the results of this analysis.

Table 66 - The Top 8 Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 2[a]	RE5Res(1)	.896	.467	3.688	1	.055	2.450	.982	6.113
	RE12Res(1)	3.078	.610	25.468	1	.000	21.718	6.571	71.781
	RP4Res(1)	.757	.464	2.660	1	.103	2.131	.858	5.292
	RP8Res(1)	.887	.468	3.585	1	.058	2.427	.969	6.075
	RP10Res(1)	1.608	.469	11.730	1	.001	4.991	1.989	12.525
	RC5Res(1)	.807	.473	2.911	1	.088	2.242	.887	5.669
	RC7Res(1)	1.197	.466	6.595	1	.010	3.312	1.328	8.259
	Constant	-2.821	.578	23.845	1	.000	.060		

a. . -2 Loglikelihood = ; Hosmer and Lemeshow Chi-square Test = 4.694, p=0.79

Table 67 - Relative Importance of Variables in the Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 2	RE5Res	-68.920	3.775	1	.052
	RE12Res	-86.997	39.928	1	.000
	RP4Res	-68.394	2.722	1	.099
	RP8Res	-68.876	3.686	1	.055
	RP10Res	-73.680	13.295	1	.000
	RC5Res	-68.526	2.986	1	.084
	RC7Res	-70.524	6.983	1	.008

One can see the developed model's loglikelihood value () in the Table 66 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.79 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the resource management area and top eight risk events. Its prediction power or accuracy was measured at 80.7%, which was greater than the naive predictor power (64.1%). (See Table 68)

Table 68 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	49	16	75.4
		Yes	17	99	85.3
	Overall Percentage				81.8
Step 2	DV	No	49	16	75.4
		Yes	19	97	83.6
	Overall Percentage				80.7

Table 69 - Validation Set

			DV		Total
			No	Yes	
RoundDV	No	Count	17	6	23
			73.9%	26.1%	100.0%
	Yes	Count	7	30	37
			18.9%	81.1%	100.0%
Total		Count	24	36	60
			40.0%	60.0%	100.0%

As previously mentioned the data was divided in two to develop and validate the model. Table 68 shows the prediction power of the model as 80.7%. It was also found that the same model correctly predicted 78.3% of the validation data (See Table 69) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 66 lists the variables in the model to forecast the degree of association on resource management and construction risk events. In light of this information showed RE5, RE12, RP4, RP8, RP10, RC5, and RC7 (Table 66) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and resource management area.

When we questioned which independent variable is critical for the top 8 risk events in the resource management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 67 indicates, removing the "Availability resources for subcontractors" (RP10) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be concluded that RC7 is the most important independent variable among the others in the model of the top 8 risk events in the resource management.

4.2.6. Communication Management Models

4.2.6.1. Engineering Model in Communication Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on communication management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only seven engineering risk events were significant, and the others (RE6, RE7, RE8, RE9, and RE11) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 70 and Table 71 summarize the results of this analysis.

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the communication management area and engineering risk events. Its prediction power or accuracy was measured at 93.4%, which was greater than the naive predictor power (54.7%). (See Table 72)

Table 70 - The Engineering Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE1Com(1)	3.454	1.032	11.206	1	.001	31.632	4.186	239.022
	RE2Com(1)	3.806	1.030	13.655	1	.000	44.963	5.973	338.465
	RE3Com(1)	2.626	.927	8.019	1	.005	13.820	2.245	85.094
	RE4Com(1)	4.439	1.075	17.048	1	.000	84.693	10.297	696.594
	RE5Com(1)	5.232	1.255	17.392	1	.000	187.110	16.005	2187.410
	RE10Com(1)	2.907	.845	11.825	1	.001	18.308	3.491	96.008
	RE12Com(1)	4.525	1.204	14.122	1	.000	92.323	8.716	977.935
	Constant	-9.566	1.865	26.317	1	.000	.000		

a. -2 Loglikelihood = 54.036; Hosmer and Lemeshow Chi-square Test =0.90 6, p=0.999

Table 71 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	Df	Sig. of the Change
Step 1	RE1Com	-35.315	16.594	1	.000
	RE2Com	-38.467	22.897	1	.000
	RE3Com	-32.578	11.119	1	.001
	RE4Com	-42.391	30.746	1	.000
	RE5Com	-46.458	38.880	1	.000
	RE10Com	-35.034	16.032	1	.000
	RE12Com	-41.025	28.014	1	.000

Table 72 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	95	4	96.0
		Yes	8	74	90.2
	Overall Percentage				93.4

Table 73 - Validation Set

Count

		DV		Total
		No	Yes	
DV	No	26	6	32
	Yes	3	25	28
Total		29	31	60

As previously mentioned the data was split in two to develop and validate the model. Table 72 shows the prediction power of the model as 93.4%. It was also found that the same model correctly predicted 85% of the validation data (See Table 73) which means the model less accurately predicts the degree of association than the naive prediction.

One can see the developed model's loglikelihood value (54.036) in the Table 70 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.999 is greater than 0.05 and supports the goodness of fit for the model.

Also, Table 70 lists the variables in the model used to predict the degree of association on communication management for engineering risk events. In light of this information, RE7, RE8, RE9, RE5, RE4, RE12 (See Table 1 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and communication management area.

When we questioned which independent variable is critical for the engineering in the communication management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 71 indicates, removing the "Late design decisions and drawings" (RE5) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RE5 is the most important independent variable among the others in the model of the engineering in the communication management.

4.2.6.2. Procurement Model in Communication Management Area

It is generally believed that procurement and communication management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on communication management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2. This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only six procurement risk events were significant, and the others (RP2, RP5, RP9, and RP10) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 74 and Table 75 summarize the results of this analysis.

Table 74 - The Procurement Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RP1Com(1)	2.391	.802	8.886	1	.003	10.925	2.268	52.626
	RP3Com(1)	4.227	.860	24.180	1	.000	68.524	12.709	369.475
	RP4Com(1)	3.800	.999	14.474	1	.000	44.699	6.311	316.586
	RP6Com(1)	3.766	.959	15.433	1	.000	43.226	6.601	283.037
	RP7Com(1)	4.682	.971	23.243	1	.000	108.029	16.100	724.874
	RP8Com(1)	3.841	.823	21.776	1	.000	46.564	9.278	233.691
	Constant	-6.725	1.220	30.398	1	.000	.001		

a. -2 Loglikelihood = 67.997; Hosmer and Lemeshow Chi-square Test = 2.021, p=0.859.

Table 75 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RP1Com	-39.518	11.040	1	.001
	RP3Com	-55.923	43.848	1	.000
	RP4Com	-45.312	22.626	1	.000
	RP6Com	-45.917	23.837	1	.000
	RP7Com	-56.261	44.526	1	.000
	RP8Com	-51.892	35.786	1	.000

As we can see the developed model's loglikelihood value (67.997) in the Table 74 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.859 is greater than 0.05 and supports the wellness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the communication management area and procurement risk events. Its prediction power or accuracy was measured at 92.3%, which was greater than the naive predictor power (52.5%). (See Table 76)

Table 76 - Classification Table

	Observed		Predicted DV No	Predicted DV Yes	Percentage Correct
Step 1	DV	No	78	8	90.7
		Yes	6	89	93.7
	Overall Percentage				92.3

Table 77 - Validation Set

Count

		DV NO	DV YES	Total
DV	NO	29	5	34
	YES	2	24	26
Total		31	29	60

As previously mentioned the data was divided in two to develop and validate the model. Table 76 shows the prediction power of the model as 92.3%. It was also found that the same model correctly predicted 88.3% of the validation data (See Table 77) that means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 74 lists the variables in the model to forecast the degree of association on communication management and procurement risk events. In light of this information showed RP1, RP3, RP4, RP6, RP7, and RP8 (Table 74) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and communication management area.

When we questioned which independent variable is critical for the procurement in the communication management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 75 indicates, removing the “Changing law or regulation” (RP7) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RP7 is the most important independent variable among the others in the model of the procurement in the communication management.

4.2.6.3. Construction Model in Communication management Area

Many people believe that the construction risk events and communication management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with communication management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the first effort, it was revealed that only twelve construction risk events were significant, and the others (RC1, RC7, RC10, RC11, RC15, and RC16) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 78 and Table 79 summarize the results of this analysis.

Table 78 - The Construction Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC2Com(1)	2.065	.907	5.183	1	.023	7.883	1.333	46.622
	RC3Com(1)	2.005	.973	4.247	1	.039	7.425	1.103	49.977
	RC4Com(1)	4.821	1.837	6.887	1	.009	124.042	3.388	4540.957
	RC5Com(1)	3.084	1.179	6.844	1	.009	21.848	2.167	220.240
	RC6Com(1)	4.443	1.222	13.219	1	.000	85.055	7.752	933.161
	RC8Com(1)	3.492	1.143	9.337	1	.002	32.838	3.498	308.313
	RC9Com(1)	3.649	1.299	7.888	1	.005	38.455	3.012	490.925
	RC12Com(1)	4.212	1.157	13.263	1	.000	67.495	6.995	651.235
	RC13Com(1)	2.123	.920	5.329	1	.021	8.353	1.378	50.645
	RC14Com(1)	2.950	.990	8.875	1	.003	19.098	2.743	132.976
	RC17Com(1)	3.962	1.424	7.743	1	.005	52.576	3.226	856.749
	RC18Com(1)	4.374	1.202	13.248	1	.000	79.346	7.528	836.365
	Constant	-14.277	3.077	21.537	1	.000	.000		

a. . -2 Loglikelihood = 47.84; Hosmer and Lemeshow Chi-square Test = 0.67; p=0.899.

Table 79 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC2Com	-26.920	5.999	1	.014
	RC3Com	-26.336	4.831	1	.028
	RC4Com	-29.020	10.199	1	.001
	RC5Com	-29.218	10.595	1	.001
	RC6Com	-36.557	25.274	1	.000
	RC8Com	-31.609	15.378	1	.000
	RC9Com	-30.133	12.425	1	.000
	RC12Com	-36.730	25.620	1	.000
	RC13Com	-27.124	6.407	1	.011
	RC14Com	-30.340	12.839	1	.000
	RC17Com	-31.175	14.508	1	.000
	RC18Com	-36.878	25.915	1	.000

As we can see the developed model's loglikelihood value (47.84) in the Table 78 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.899 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the communication management area and construction risk events. Its prediction power or accuracy was measured at 95%, which was greater than the naive predictor power (51.4%). (See Table 80)

Table 80 - Classification Table

	Observed		Predicted: DV NO	Predicted: DV YES	Predicted: Percentage Correct
Step 1	DV	NO	84	4	95.5
		YES	5	88	94.6
	Overall Percentage				95.0

Table 81 - Validation Set

Count

		DV NO	DV YES	Total
DV	NO	27	4	31
	YES	1	28	29
Total		28	32	60

As previously mentioned the data was divided in two to develop and validate the model. Table 80 shows the prediction power of the model as 95%. It was also found that the same model correctly predicted 91.7% of the validation data (see Table 81) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 78 lists the variables in the model to forecast the degree of association on communication management and construction risk events. In light of this information showed RC2, RC3, RC4, RC5, RC6, RC8, RC9, RC12, RC13, RC14, RC17, RC18 a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and communication management area.

When we questioned which independent variable is critical for the construction in the communication management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 79 indicates, removing the "Unethical work practices" (RC18) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RC18 is the most important independent variable among the others in the model of the construction in the communication management.

4.2.6.4. Top 8 Risk Events Model in Communication Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one which includes RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, Table2, and Table3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with communication management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the FIRST effort, it was revealed that only six risk events were significant, and the RP4 and RP8 were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 82 and Table 83 summarize the results of this analysis.

Table 82 - The Top 8 Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE5Com(1)	1.255	.443	8.020	1	.005	3.507	1.472	8.359
	RE8Com(1)	1.926	.681	8.003	1	.005	6.859	1.807	26.042
	RE12Com(1)	.986	.417	5.595	1	.018	2.680	1.184	6.065
	RP10Com(1)	1.985	.643	9.516	1	.002	7.278	2.062	25.688
	RC5Com(1)	1.534	.406	14.258	1	.000	4.636	2.091	10.278
	RC7Com(1)	1.740	.480	13.145	1	.000	5.698	2.224	14.597
	Constant	-2.451	.404	36.814	1	.000	.086		

a. -2 Loglikelihood = 158.5 ; Hosmer and Lemeshow Chi-square Test = 11.753, p=0.109.

One can see the developed model’s loglikelihood value (158.5) in the Table 82 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.109 is greater than 0.05 and supports the goodness of fit for the model.

Table 83 - Relative Importance of Variables in the Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE5Com	-83.397	8.295	1	.004
	RE8Com	-83.935	9.371	1	.002
	RE12Com	-82.115	5.731	1	.017
	RP10Com	-84.911	11.323	1	.001
	RC5Com	-86.880	15.261	1	.000
	RC7Com	-86.514	14.529	1	.000

After the process was examined, the model at the first step showed the best at predicting the degree of association among the communication management area and top eight risk events. Its prediction power or accuracy was measured at 78.5%, which was greater than the naive predictor power (50.3%). (See Table 84)

Table 84 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			NO	YES	
Step 1	DV	NO	71	20	78.0
		YES	19	71	78.9
	Overall Percentage				78.5

Table 85 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	29	6	35
	YES	8	17	25
Total		37	23	60

As previously mentioned the data was divided in two to develop and validate the model. Table 84 shows the prediction power of the model as 78.5%. It was also found that the same model correctly predicted 76.7% of the validation data (See Table 85) and there is not too much difference between the model and validation. Thus, we can ignore the gap which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 66 lists the variables in the model to forecast the degree of association on communication management and construction risk events. In light of this information showed RE5, RE8, RE12, RP10, RC5, and RC7 (Table 82) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and communication management area.

When we questioned which independent variable is critical for the top 8 risk events in the communication management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 83 indicates, removing the "Delay in decision making and approval" (RC5) variable from the model changes the loglikelihood value more than other values in the model therefore, it can be conclude that RC5 is the most important independent variable among the others in the model of the top 8 risk events in the communication management.

4.2.7. Safety Management Models

4.2.7.1. Engineering Model in Safety Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on safety management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model. We began our analysis with the "stepwise backward LR" method. First, it was revealed that only five engineering risk events were significant, and the others (RE2, RE4, RE6, RE8, RE9, RE10, and RE11) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 86 and Table 87 summarize the results of this analysis.

Table 86 - The Engineering Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE1Com(1)	3.454	1.032	11.206	1	.001	31.632	4.186	239.022
	RE2Com(1)	3.806	1.030	13.655	1	.000	44.963	5.973	338.465
	RE3Com(1)	2.626	.927	8.019	1	.005	13.820	2.245	85.094
	RE4Com(1)	4.439	1.075	17.048	1	.000	84.693	10.297	696.594
	RE5Com(1)	5.232	1.255	17.392	1	.000	187.110	16.005	2187.410
	RE10Com(1)	2.907	.845	11.825	1	.001	18.308	3.491	96.008
	RE12Com(1)	4.525	1.204	14.122	1	.000	92.323	8.716	977.935
	Constant	-9.566	1.865	26.317	1	.000	.000		

a. -2 Loglikelihood = 54.036; Hosmer and Lemeshow Chi-square Test =0.90 6, p=0.999.

Table 87 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE1Saf	-57.387	7.678	1	.006
	RE3Saf	-64.683	22.270	1	.000
	RE5Saf	-61.782	16.468	1	.000
	RE7Saf	-65.862	24.630	1	.000
	RE11Saf	-59.859	12.622	1	.000

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the safety management area and engineering risk events. Its prediction power or accuracy was measured at 89%, which was greater than the naive predictor power (78.1%). (See Table 88)

Table 88 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			NO	YES	
Step 1	DV	NO	124	6	95.4
		YES	14	37	72.5
	Overall Percentage				89.0

Table 89 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	41	7	48
	YES	4	8	12
Total		45	15	60

As previously mentioned the data was split in two to develop and validate the model. Table 89 shows the prediction power of the model as 89%. It was also found that the same model correctly predicted 81% of the validation data (See Table 89) which means the model less accurately predicts the degree of association than the naive prediction.

One can see the developed model's loglikelihood value (107.095) in the Table 86 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.978 is greater than 0.05 and supports the goodness of fit for the model.

Also, Table 86 lists the variables in the model used to predict the degree of association on safety management for engineering risk events. In light of this information, RE1, RE3, RE5, RE7, and RE11 (See Table 1 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and safety management area.

When we questioned which variable is critical for the engineering phase in the safety management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 87 indicates, removing the "Fast tracking or crashing for accelerating time" (RE7) variable from the model changes the loglikelihood value less than other values in the model therefore, it can be concluded that RE7 is the least important variable among the others in the model of the engineering phase in the safety management.

4.2.7.2. Procurement Model in Safety Management Area

It is generally believed that procurement and safety management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on safety management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2. This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only six procurement risk events were significant, and the others (RP1, RP6, RP9, and RP10) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 90 and Table 91 summarize the results of this analysis

Table 90 - The Procurement Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	RP2Saf(1)	4.319	1.187	13.233	1	.000	75.108	7.329	769.662
	RP3Saf(1)	6.447	1.612	15.996	1	.000	630.832	26.779	14860.282
	RP4Saf(1)	4.464	1.158	14.863	1	.000	86.845	8.977	840.193
	RP5Saf(1)	4.860	1.085	20.046	1	.000	129.012	15.371	1082.857
	RP7Saf(1)	2.808	.911	9.511	1	.002	16.583	2.783	98.815
	RP8Saf(1)	3.606	1.105	10.650	1	.001	36.831	4.222	321.269
	Constant	-7.780	1.690	21.196	1	.000	.000		

a. -2 Loglikelihood = 60.414; Hosmer and Lemeshow Chi-square Test = 0.211, p=0.851.

Table 91 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RP2Saf	-43.082	25.749	1	.000
	RP3Saf	-51.584	42.754	1	.000
	RP4Saf	-41.906	23.397	1	.000
	RP5Saf	-49.173	37.932	1	.000
	RP7Saf	-36.753	13.092	1	.000
	RP8Saf	-36.702	12.990	1	.000

As we can see the developed model's loglikelihood value (60.414) in the Table 90 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.851 is greater than 0.05 and supports the wellness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the safety management area and procurement risk events. Its prediction power or accuracy was measured at 92.8%, which was greater than the naive predictor power (64.6%). (See Table 92)

Table 92 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			No	Yes	
Step 1	DV	No	111	6	94.9
		Yes	7	57	89.1
	Overall Percentage				92.8

Table 93 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	38	3	41
	YES	6	13	19
Total		44	16	60

As previously mentioned the data was divided in two to develop and validate the model. Table 92 shows the prediction power of the model as 92.8%. It was also found that the same model correctly predicted 85% of the validation data (See Table 93) that means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 90 lists the variables in the model to forecast the degree of association on safety management and procurement risk events. In light of this information showed RP2, RP3, RP4, RP5, RP7, and RP8 (Table 90) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and safety management area.

When we questioned which variable is critical for the P in the safety management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is .As Table 91 indicates, removing the "Contract gaps" (RP3) variable from the model changes the loglikelihood value less than other values in the model, therefore, it can be concluded that RP3 is the least important variable among the others in the model of the procurement phase in the safety management.

4.2.7.3. Construction Model in Safety Management Area

Many people believe that the construction risk events and safety management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with safety management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases and the remaining 25% (60) was used to validate the model.

The "stepwise backward LR" method was selected for the model analysis. In the first effort, it was revealed that only eight construction risk events were significant, and the others (RC3, RC4, RC5, RC7, RC10, RC12, RC15, RC16, RC17, and RC18) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 94 and Table 95 summarize the results of this analysis.

Table 94 - The Construction Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC1Saf(1)	3.440	.803	18.334	1	.000	31.181	6.458	150.555
	RC2Saf(1)	1.810	.816	4.917	1	.027	6.110	1.234	30.260
	RC6Saf(1)	3.753	.986	14.483	1	.000	42.637	6.172	294.541
	RC8Saf(1)	2.991	.833	12.885	1	.000	19.912	3.889	101.968
	RC9Saf(1)	2.037	.738	7.607	1	.006	7.664	1.803	32.583
	RC11Saf(1)	3.166	1.009	9.855	1	.002	23.719	3.285	171.236
	RC13Saf(1)	3.063	1.209	6.424	1	.011	21.396	2.002	228.622
	RC14Saf(1)	3.504	1.168	9.004	1	.003	33.244	3.371	327.825
	Constant	-4.232	.816	26.929	1	.000	.015		

a. -2 Loglikelihood = 76.266; Hosmer and Lemeshow Chi-square Test = 4.005; p=0.815.

Table 95 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC1Saf	-52.583	28.901	1	.000
	RC2Saf	-40.938	5.610	1	.018
	RC6Saf	-50.576	24.886	1	.000
	RC8Saf	-46.905	17.545	1	.000
	RC9Saf	-42.603	8.941	1	.003
	RC11Saf	-44.748	13.230	1	.000
	RC13Saf	-41.495	6.724	1	.010
	RC14Saf	-46.318	16.369	1	.000

As we can see the developed model's loglikelihood value (76.266) in the Table 78 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.815 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the safety management area and construction risk events. Its prediction power or accuracy was measured at 91.7%, which was greater than the naive predictor power (60.2%). (See Table 96)

Table 96 - Classification Table

	Observed		Predicted: DV NO	Predicted: DV YES	Predicted: Percentage Correct
Step 1	DV	NO	65	7	90.3
		YES	8	101	92.7
	Overall Percentage				91.7

Table 97 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	12	10	22
	YES	0	38	38
Total		12	48	60

As previously mentioned the data was divided in two to develop and validate the model. Table 96 shows the prediction power of the model as 91.7%. It was also found that the same model correctly predicted 83.3% of the validation data (See Table 97) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 94 lists the variables in the model to forecast the degree of association on safety management and construction risk events. In light of this information showed RC1, RC2, RC6, RC8, RC9, RC11, RC13, RC14 a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and safety management area.

When we questioned which variable is critical for the construction phase in the safety management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 95 indicates, removing the “Differing site condition” (RC1) variable from the model changes the loglikelihood value less than other values in the model, therefore, it can be concluded that

RC1 is the most important variable among the others in the model of the construction phase in the safety management.

4.2.7.4. Top 8 risk Events Model in Safety Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, Table2, and Table3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with safety management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the third effort, it was revealed that only six risk events were significant, and the RP4 and RP8 were found to be insignificant. Therefore, a FOURTH effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the THIRD step. The analysis was performed at p=0.05 significance level to create the model. Table 98 and Table 99 summarize the results of this analysis.

Table 98 - The Top 8 Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 3[a]	RE5Saf(1)	2.371	.754	9.881	1	.002	10.710	2.442	46.973
	RE8Saf(1)	3.614	1.204	9.005	1	.003	37.129	3.503	393.495
	RE12Saf(1)	1.619	.498	10.568	1	.001	5.046	1.902	13.390
	RP4Saf(1)	3.160	.708	19.915	1	.000	23.582	5.885	94.496
	RP8Saf(1)	1.364	.689	3.923	1	.048	3.911	1.014	15.082
	RC7Saf(1)	1.928	.532	13.131	1	.000	6.877	2.424	19.515
	Constant	-3.482	.518	45.197	1	.000	.031		

a. -2 Loglikelihood = 115.521; Hosmer and Lemeshow Chi-square Test = 7.874, p=0.247.

Table 99 - Relative Importance of Variables in The Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 3	RE5Saf	-63.196	10.870	1	.001
	RE8Saf	-65.676	15.830	1	.000
	RE12Saf	-63.366	11.210	1	.001
	RP4Saf	-70.462	25.403	1	.000
	RP8Saf	-59.813	4.105	1	.043
	RC7Saf	-65.360	15.199	1	.000

One can see the developed model's loglikelihood value (115.52) in the Table 82 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.247 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the third step showed the best at predicting the degree of association among the safety management area and top eight risk events. Its prediction power or accuracy was measured at 86.7%, which was greater than the naive predictor power (63.5%). (See Table 100)

Table 100 - Classification Table

			Predicted		
			DV		Percentage Correct
	Observed		NO	YES	
Step 3	DV	NO	103	12	89.6
		YES	12	54	81.8
	Overall Percentage				86.7

Table 101 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	30	8	38
	YES	8	14	22
Total		38	22	60

As previously mentioned the data was divided in two to develop and validate the model. Table 100 shows the prediction power of the model as 86.7%. It was also found that the same model correctly predicted 73.3% of the validation data (See Table 101) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 98 lists the variables in the model to forecast the degree of association on safety management and construction risk events. In light of this information showed RE5, RE8, RE12, RP4, RP8, and RC7 (Table 98) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and safety management area.

When we questioned which variable is critical for the top 8 risk events in the safety management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 99 indicates, removing the “changing market condition” (RP4) variable from the model changes the loglikelihood value less than other values in the model, therefore, it can be concluded that RP4 is the most important variable among the others in the model of the top8 risk events in the safety management.

4.2.8. Cost Management Models

4.2.8.1. Engineering Model in Cost Management Area

The intent was to provide a model that could be used to predict the degree of relationship (association) of engineering risk events on cost management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of twelve engineering risk events (RE1, RE2… RE12). This subset was extracted from the main dataset by classifying the independent variables. As discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

We began our analysis with the "stepwise backward LR" method. First, it was revealed that only five engineering risk events were significant, and the others (RE1, RE2, RE4, RE6, RE10, RE11, and RE12) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 102 and Table 103 summarize the results of this analysis.

Table 102 - The Engineering Model Results

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RE3C(1)	4.671	1.663	7.887	1	.005	106.790	4.100	2781.523
	RE5C(1)	4.171	1.277	10.669	1	.001	64.778	5.303	791.327
	RE7C(1)	2.942	1.174	6.280	1	.012	18.963	1.898	189.411
	RE8C(1)	2.644	1.260	4.406	1	.036	14.067	1.191	166.102
	RE9C(1)	5.980	1.844	10.512	1	.001	395.573	10.646	14698.280
	Constant	-5.129	1.552	10.919	1	.001	.006		

a. -2 Loglikelihood = 35.453; Hosmer and Lemeshow Chi-square Test = 2.15, p=0.976

Table 103 - Relative Importance of Variables in the Engineering Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RE3C	-25.937	16.421	1	.000
	RE5C	-28.093	20.733	1	.000
	RE7C	-22.573	9.693	1	.002
	RE8C	-20.805	6.156	1	.013
	RE9C	-30.907	26.362	1	.000

When we closely examined the process, the model at the first step was the best at predicting the degree of association among the cost management area and engineering risk events. Its prediction power or accuracy was measured at 95.6%, which was greater than the naive predictor power (86.7%). (See Table 104)

Table 104 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			NO	YES	
Step 1	DV	NO	18	6	75.0
		YES	2	155	98.7
	Overall Percentage				95.6

Table 105 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	3	2	5
	YES	0	55	55
Total		3	57	60

As previously mentioned the data was split in two to develop and validate the model. Table 104 shows the prediction power of the model as 95.6%. It was also found that the same model correctly predicted 96.7% of the validation data (See Table 105) which means the model more accurately predicts the degree of association than the naive prediction.

One can see the developed model's loglikelihood value (35.453) in the Table 102 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.976 is greater than 0.05 and supports the goodness of fit for the model.

Also, Table 102 lists the variables in the model used to predict the degree of association on cost management for engineering risk events. In light of this information, RE3, RE5, RE7, RE8, and RE9 (see Table 1 for the risk events name) showed a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the engineering phase of a construction project and cost management area.

When we questioned which variable is critical for the engineering in the cost management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 103 indicates, removing the "Inadequate time scheduling" (RE9) variable from the model changes the loglikelihood value less than other values in the model, therefore, it can be concluded that RE9 is the most important variable among the others in the model of the engineering phase in the cost management.

4.2.8.2. Procurement Model in Cost Management Area

It is generally believed that procurement and cost management have a strong relationship. In this part, we examined this theory by using binary logistic regression to predict the degree of relationship (association) of procurement risk events on cost management in construction projects. Thus, we ran a binary logistic regression analysis for a subset consisting of ten procurement risk events (RP1, RP2… RP10) as Table 2.

This subset was extracted from the main dataset by classifying the independent variables. Again, as discussed previously in the methodology section, the 241 cases subsets were divided into two sections: the model development data set, which is 75% (181 cases) of the 241 total cases and the remaining 25% (60) was used to validate the model.

We started with the "stepwise backward conditional" method to our analysis. The model iteration was stopped at the sixth step. It was revealed that only five procurement risk events were significant, and the others (RP1, RP2, RP5, RP9, and RP10) were found to be insignificant. The analysis was performed at p=0.05 significance level to create the model. Table 106 and Table 107 summarize the results of this analysis

Table 106 - The Procurement Model Results

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 6	RP3C(1)	3.194	.916	12.146	1	.000	24.376	4.046	146.874
	RP4C(1)	2.512	.812	9.568	1	.002	12.331	2.510	60.572
	RP6C(1)	2.408	.958	6.322	1	.012	11.117	1.701	72.670
	RP7C(1)	2.058	1.031	3.980	1	.046	7.827	1.037	59.080
	RP8C(1)	3.096	1.079	8.229	1	.004	22.100	2.666	183.196
	Constant	-2.456	.803	9.356	1	.002	.086		

a. -2 Loglikelihood = 54.703; Hosmer and Lemeshow Chi-square Test = 1.242, p=0.990.

Table 107 - Relative Importance of Variables in the Procurement Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 6	RP3C	-36.812	18.920	1	.000
	RP4C	-33.600	12.497	1	.000
	RP6C	-31.691	8.678	1	.003
	RP7C	-29.888	5.072	1	.024
	RP8C	-33.589	12.474	1	.000

As we can see the developed model's loglikelihood value (54.703) in the Table 106 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of is greater than 0.05 and supports the wellness of fit for the model.

After the process was examined, the model at the six steps showed the best at predicting the degree of association among the cost management area and procurement risk events. Its prediction power or accuracy was measured at 92.3%, which was greater than the naive predictor power (88.4%). (See Table 108)

Table 108 - Classification Table

		Predicted		
		DV		Percentage
	Observed	NO	YES	Correct
Step 6	NO	10	11	47.6
	YES	3	157	98.1
				92.3

Table 109 -Validation Set

Count

		DV		
		NO	YES	Total
DV	NO	3	1	4
	YES	2	54	56
Total		5	55	60

As previously mentioned the data was divided in two to develop and validate the model. Table 108 shows the prediction power of the model as 92.3%. It was also found that the same model correctly predicted 95.0% of the validation data (See Table 109) that

means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 106 lists the variables in the model to forecast the degree of association on cost management and procurement risk events. In light of this information showed RP3, RP4, RP6, RP7, and RP8 (Table 106) a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the procurement phase of a construction project and cost management area.

When we questioned which independent variable is critical for the procurement in the cost management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 107 indicates, removing the "Contract gaps" (RP3) variable from the model changes the loglikelihood value more than other values in the model, therefore, it can be concluded that RP3 is the most important independent variable among the others in the model of the procurement in the cost management.

4.2.8.3. Construction Model in Cost Management Area

Many people believe that the construction risk events and cost management have a strong relationship. In this part, we tested this theory by utilizing binary logistic regression model to predict the degree of relationship (association) for construction risk events with cost management in construction projects. Therefore, we ran a binary logistic regression analysis for a subset consisting of eighteen construction risk events (RC1, RC2… RC18) as Table 2. This subset was extracted from the main dataset by categorizing the independent variables. Besides, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the first effort, it was revealed that only five construction risk events were significant, and the others (RC2, RC3, RC5, RC6, RC7, RC8, RC9, RC10, RC11, RC13, RC16, RC17, and RC18) were found to be insignificant. Therefore, a secondary effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the first step. The analysis was performed at p=0.05 significance level to create the model. Table 110 and Table 111 summarize the results.

As we can see the developed model’s loglikelihood value (32.462) in the Table 110 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.999 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the first step showed the best at predicting the degree of association among the cost management area and construction risk events. Its prediction power or accuracy was measured at 96.1%, which was greater than the naive predictor power (83.4%). (See Table 112)

Table 110 - The Construction Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	RC1C(1)	3.674	1.267	8.406	1	.004	39.395	3.288	472.043
	RC4C(1)	4.635	1.505	9.491	1	.002	103.066	5.399	1967.362
	RC12C(1)	5.886	1.751	11.298	1	.001	359.912	11.632	11135.916
	RC14C(1)	4.224	1.475	8.198	1	.004	68.286	3.790	1230.297
	RC15C(1)	7.141	2.392	8.916	1	.003	1263.109	11.633	137152.148
	Constant	-7.637	2.310	10.927	1	.001	.000		

a. -2 Loglikelihood = 32.462; Hosmer and Lemeshow Chi-square Test = 0.59; p=0.999.

Table 111 - Relative Importance of Variables in the Construction Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	RC1C	-22.987	13.513	1	.000
	RC4C	-26.528	20.594	1	.000
	RC12C	-31.784	31.105	1	.000
	RC14C	-24.376	16.289	1	.000
	RC15C	-29.607	26.752	1	.000

Table 112 - Classification Table

	Observed		Predicted		
			DV		Percentage Correct
			NO	YES	
Step 1	DV	NO	25	5	83.3
		YES	2	149	98.7
	Overall Percentage				96.1

Table 113 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	7	2	9
	YES	3	48	51
Total		10	50	60

As previously mentioned the data was divided in two to develop and validate the model. Table 112 shows the prediction power of the model as 96.1%. It was also found that the same model correctly predicted 91.7% of the validation data (See Table 113) which means the model less accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 110 lists the variables in the model to forecast the degree of association on cost management and construction risk events. In light of this information showed RC1, RC4, RC12, RC14, and RC15 a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and cost management area.

When we questioned which variable is critical for the construction in the cost management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 111 indicates, removing the “Union labor influence and labor strike” (RC12) variable from the model changes the loglikelihood value less than other values in the model therefore, it can be conclude that RC12 is the most important variable among the others in the model of the construction phase in the cost management.

4.2.8.4. Top 8 Risk Events Model in Cost Management Area

As we explained previously, two surveys were conducted in this research. Based on the Pareto principle, 20% top risk events (equal 8 from 40 risk events) were selected from the result of Survey one wich include RE5, RE8, RE12, RP4, RP8, RP10, RC5, and RC7 (See Table1, Table2, and Table3 for their names). In this section, a binary logistic regression model ran to predict the degree of relationship (association) for top eight risk events with cost management in construction projects. Additionally, as discussed previously in the methodology section, the 241 cases subsets were split into two portions; model development data set, which is 75% (181 cases) of the 241 total cases, and the remaining 25% (60) was used to validate the model.

The “stepwise backward LR” method was selected for the model analysis. In the third effort, it was revealed that only six risk events were significant, and the RE8 and RP8 were found to be insignificant. Therefore, a fourth effort took place by removing insignificant risk events and using only the significant risk events for modeling. The model iteration was stopped at the THIRD step. The analysis was performed at p=0.05 significance level to create the model. Table 114 and Table 115 summarize the results of this analysis.

Table 114 - The Top 8 Model Results

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 3[a]	RE5C(1)	1.119	.687	2.654	1	.103	3.062	.797	11.771
	RE12C(1)	1.689	.913	3.424	1	.064	5.413	.905	32.387
	RP4C(1)	1.743	.694	6.304	1	.012	5.713	1.466	22.267
	RP10C(1)	1.268	.746	2.892	1	.089	3.555	.824	15.331
	RC5C(1)	2.370	.837	8.014	1	.005	10.701	2.073	55.226
	RC7C(1)	3.288	1.103	8.886	1	.003	26.791	3.084	232.760
	Constant	-2.295	.796	8.324	1	.004	.101		

a. -2 Loglikelihood = 58.069; Hosmer and Lemeshow Chi-square Test = 2.104, p=0.978.

Table 115 - Relative Importance of Variables in The Top 8 Model

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 3	RE5C	-30.413	2.756	1	.097
	RE12C	-31.104	4.138	1	.042
	RP4C	-32.444	6.820	1	.009
	RP10C	-30.593	3.117	1	.077
	RC5C	-34.325	10.581	1	.001
	RC7C	-37.483	16.897	1	.000

One can see the developed model's loglikelihood value (58.069) in the Table 114 footnote. When we took up the question of the goodness of fit for the model, the Hosmer and Lemeshow test revealed that the data fits the model satisfactorily. A poor fit is indicated by a significance value of less than 0.05; hence, the significance value of 0.978 is greater than 0.05 and supports the goodness of fit for the model.

After the process was examined, the model at the third step showed the best at predicting the degree of association among the cost management area and top eight risk events. Its prediction power or accuracy was measured at 93.9%, which was greater than the naive predictor power (88.4%). (See Table 116)

Table 116 - Classification Table

			Predicted		
			DV		Percentage
	Observed		NO	YES	Correct
Step 3	DV	NO	12	9	57.1
		YES	2	158	98.8
	Overall Percentage				93.9

Table 117 - Validation Set

Count

		DV		Total
		NO	YES	
DV	NO	3	1	4
	YES	2	54	56
Total		5	55	60

As previously mentioned the data was divided in two to develop and validate the model. Table 116 shows the prediction power of the model as 93.9%. It was also found that the same model correctly predicted 95% of the validation data (See Table 117) which means the model more accurately predicts the degree of association than the naive prediction.

In the final analysis, Table 114 lists the variables in the model to forecast the degree of association on cost management and construction risk events. In light of this information showed RE5, RE12, RP4, RP10, RC5, and RC7 a statistically significant effect on the degree of association. By examining the ß coefficients, it was revealed that all variables in the model have an increasing impact on the association between the construction phase and cost management area.

When we questioned which variable is critical for the top 8 risk events in the cost management model, we used the change in the loglikelihood values an indicator. Higher the change in this indicator more important the variable is. As Table 115 indicates, removing the “Fast tracking or crashing for accelerating time schedule” (RC7) variable from the model changes the loglikelihood value less than other values in the model therefore, it can be concluded that RC7 is the most important variable among the others in the model of top risk events in the cost management.

CHAPTER 5 - CONCLUSION

We conclude in this chapter with a discussion of the results and implications of our modeling strategies, as well as potential future work.

The study presented in this dissertation was undertaken to analyze the risk propagation among engineering, procurement, and construction phases of construction projects. For this purpose, Survey One was conducted to obtain responses to a set of questions (see Appendix A) from 103 participants. Next, we analyzed the survey data by using sensitivity analysis through radar and tornado diagrams. Based on the analysis of these results we can conclude that:

"Late design decision and drawings" (RE5) is the most critical risk of an engineering phase and one which has the greatest impact on other phases (procurement and construction phases). In addition, "Availability of resources for subcontractors" (RP10) has the greatest impact on other phases (engineering and construction phases). Also, "Delay in decision making and approval" (RC5) has the greatest effect on other phases (engineering and procurement phases). Finally, according to this sensitive analysis, "late design decisions and drawings" (RE5) is the most important risk event among a total of forty risk events covered in this study, in terms of risk propagation to other phases. Additionally, the results show us that P-C is the strongest risk event propagation relationship in construction projects. In other words, procurement risk events have the greatest impact on the construction phase.

Also, using Survey Two, we developed twenty-eight models to understand interrelationship among the risk events in these three phases and project management areas. In Survey Two, we asked 241 practitioners to answer a set of new questions (see Appendix B). Then, the data was used to create twenty-eight models by utilizing the binary logistic regression model. The results indicated that the risk events in the engineering, procurement, and construction phases can strongly impact project management areas such as scope, time, cost, quality, communication, resource, and safety. Based on logistic regression analysis results, it was concluded that different predictive models can be developed to identify the association between the different risk events from different phases of construction projects and the project management categories.

To sum up briefly, a total of 28 modeling efforts were initiated to understand the relationship among the seven project management areas and the risk events to project phases. Table 118 summarizes each modeling attempt and their predictive power as well as the validation results. As one can see from the table, nineteen models were created and was validated successfully, for the remaining nine models the validation attempts were not successful, meaning that the models created were not able to predict the outcome as successfully as originally created models.

Also, the most critical risk events among the construction phases and the project management areas were identified for each model. These may give the project risk management professionals an opportunity to evaluate the projects for occurrence these events and take appropriate action for avoiding them.

Table 118 - Summary of the Models' Result

PMA	Engineering			Procurement			Construction			Top 8		
Time	RE7	94%	90%	RP10	95%	98%	RC9	96%	92%	RP10	89%	85%
Scope	RE4	91%	95%	RP1	87%	80%	RC5	90%	82%	RP8	80%	83%
Quality	RE12	95%	93%	RP8	96%	93%	RC2	85%	80%	RC5	86%	81%
Resource	RE5	87%	78%	RP10	94%	90%	RC7	94%	83%	RP10	80%	78%
Communication	RE5	93%	85%	RP7	92%	88%	RC1	95%	90%	RC5	78%	77%
Safety	RE7	89%	76%	RP3	92%	85%	RC1	91%	83%	RP4	86%	73%
Cost	RE9	95%	97%	RP3	92%	95%	RC1	96%	92%	RC7	94%	95%

According to Table 118, the risk event RP10 "Availability of resources for subcontractors" has the greatest impact on project management models since Table 118 shows us it is the most important risk event of the four models.

As mentioned previously, a resource can be equipment or machine, human resource, and/or material. There is no doubt that shortage or lack of any type of the resource can have an impact on objectives of construction projects, such as time, cost, quality, and scope. In many cases, subcontractors promise in their contract to provide enough resources on time in their contract, but many times they do not. Unskilled employee and inappropriate equipment or poor-quality material are causes of rework, safety hazards, delay, more cost, and reputation loss.

Also, one can see that risk event RC5 "Delay in decision making and approval" is very impactful on the project management areas (PMA) since it has the greatest impact on three binary logistic regression models (Table 118). Decision making and approval are critical milestones in construction projects. In a large number of cases, delay in approval activities by owner and inspectors, or even delay in notification decisions to stakeholders, can stop or delay the execution of project activities. Thus, this risk can strongly affect attaining project management objectives, such as time and cost.

Additionally, risk events RE5 “Late design decision and drawings” is one of the important risk events because it has the greatest impact on two engineering risk models. Overall, the cause of delay in construction projects can be due to delay in design activities and drawings delivery, even though the design cost is a small portion of the construction project cost. This risk event from engineering phase propagates to procurement and construction phases and may affect the productivity of other project participants who are engaged in procurement or construction phase activities.

RP10 “Availability of resources for subcontractors” is found to be the most important risk event for time management and resource management areas. Resource includes equipments, material, and human which can impact on the success of any project directly.

RC5 “Delay in decision making and approval” is the most critical risk event for communication management and quality management areas.

RC7 “Fast tracking and crashing for accelerating time schedule” showed strongly impact on the cost management. The project managers should consider this events and it’s consequences on cost before they decide to pursue.

In the final analysis, the findings from the Survey One are confirmed and support with the findings of Survey Two. Both data analysis indicated that RP10, RC5, RE5 are the most important risk events in engineering, procurement, and construction phases, and they have relatively more impact on the seven project management areas. Also, information published in the Smart Market Reports (2011 and2014) support these findings.

Recommendations

For future research, we recommend carrying out odds ratio and logistic regression modeling on each of the seven project management areas (scope management, time management, cost management, quality management, resource management, communication management, and safety management). Another future consideration would be developing models for each phase of the construction project, i.e. engineering, procurement, and construction.

Additionally, similar studies can be performed by selecting different project management areas such as environment management and stakeholder management.

Also, future research can focus on the risk events ranking high in the engineering, procurement, and construction phases. In addition, the risk propagation models develop in this study can be extended into other industries such as manufacturing or automotive fields. Furthermore, there is an opportunity to focus more on a particular type of construction projects such as infrastructure or commercial sectors.

Likewise, in this study, we used binary logistic regression to understand the relationship among risk events and project management areas. Lastly, future investigators might like to examine different research techniques and methods to model risk propagation in construction projects, such as Bayesian Networks (BN) and Artificial Neural Network (ANN).

We recommend to practitioners that more focus should be on the project's risk propagation management rather than other construction project management areas. From the initial phase of a construction project, the project management team should identify high-level risks. Simultaneously, they should also create a risk propagation management plan that covers the identified risk events. After evaluating their propagation scores; risk management team should define a response plan for critical ones in the planning phase. Consequently, they should control risk propagation based on the risk plan during the project life cycle. These mentioned risk events can affect project objectives of construction projects.

Additionally, practitioners can use the results of this research for future projects. They should ensure the availability of resources of subcontractors include equipment, material, labors during procurement phase. Also, they should accelerate decision making and approval during construction phase and they should provide drawings and technical documents according to the project schedule.

Likewise, switching from one phase to another phase is very critical milestone (gate phasing) for one project. Thus, the relationships among the E, P, and C phases are very important in construction projects. The P-C and E-C are the strongest link among construction phases. In other words, procurement and engineering risk events events have the greatest impact on the construction phase. Therefore, the project teams and project managers should more monitor these risk events.

APPENDIX A – SURVEY ONE

Appendix A
Survey One
Risk Propagation Survey

1. What is your highest educational background?

- ◯ 6 years college or more
- ◯ 4 years college
- ◯ 2 years college
- ◯ Other (please specify)

2. How many years of project experience do you have?

- ◯ Less than 5 years
- ◯ 5 to 10 years
- ◯ 10 to 15 years
- ◯ More than 15 years

3. What has been your typical role in previous projects?

- ☐ Project Manager
- ☐ PMO Team Member
- ☐ Risk Management Expert
- ☐ Project Control Expert
- ☐ Project Engineer
- ☐ Educator or Trainer
- ☐ Other (please specify)

4. What is the average value of your projects have worked? (X= Budget amount, m: millions)

- [ ] X < $10 m
- [ ] $10 m < X < $ 50 m
- [ ] $ 50 m < X < $ 100 m
- [ ] $ 100 m < X < $ 500 m
- [ ] X > $ 500 m

5. What type of the projects have you been involved most frequently?

- [ ] Industrial
- [ ] Housing
- [ ] Energy Sector
- [ ] Infrastructure
- [ ] Commercial
- [ ] Other (please specify)

6. In what part of the world have your projects been constructed?

- [ ] US & Canada
- [ ] Central & South America
- [ ] Europe
- [ ] Middle East
- [ ] Asia & Oceania
- [ ] Africa

Appendix A
Survey One
Risk Propagation Survey

7. Majority of the typical negative Engineering (E) risk events (Threat) are listed below.
Please determine impact and probability of them on Procurement (P) or Construction (C).

	Probability	Impact on ***Procurement (P)***	Impact on ***Construction (C)***
Design errors or ommisions			
Misinterpretation of technical documents			
Error to update technical and project documents			
Errors and ommisions in shop drawings			
Late design decisions and drawings			
Inadequate quality planning			
Inadequate resource planning			
Inadequate budget estimation			
Inadequate time scheduling			
Unclear scope			

Comments (please specify)

8. Some of the typical positive Engineering (E) risk events (Opportunity) are listed below.
Please determine impact and probability of them on Procurement (P) or Construction (C).

	Probability	Impact on ***Procurement (P)***	Impact on ***Construction (C)***
Using BIM in design			
Using lesson learned in design			

Comments (please specify)

9. Majority of the typical negative Procurement (P) risk events (Threat) are listed below.
Please determine impact and probability of them on Engineering (E) or Construction (C).

	Probability	Impact on ***Engineering (E)***	Impact on ***Construction (C)***
Errors in bidding process			
Selecting unskilled supplier and subcontractor			
Contract gaps			
changing market condition			
Changing currency rate			
Lead time change (material delivery)			
Changing law or regulation			
Inadequate change management process			
Payment delay			
Availability resources of subcontractors			

Comments (please specify)

10. Majority of the typical negative Construction (C) risk events (Threat) are listed below.
Please determine impact and probability of them on Procurement (P) or Engineering (E).

	Probability	Impact on ***Engineering (E)***	Impact on ***Procurement (P)***
Differing site condition			
Responsibility gaps between prime (contractor) and subcontractors			
New user function or technology request			
Scope creep			
Delay in decision making and approval			
Contractor caused delay			
Fast tracking or crashing for accelerating time schedule			
Using wrong reference specs, codes or standards			
Inadequate resource supervising			
Unskilled employees			
Inadequate site delivery and storage			
Labor strike and Union labor influence			
Owner's organization and personnel change			
Inadequite control system			
Job site security			
Construction pollution and environmental degradation			
Safety hazards			
Unethical work practices			

Comments (please specify)

APPENDIX B – SURVEY TWO

Appendix B
Survey Two
EPC & PMA

1. What is your highest educational background?

- ◯ 6 years college or more
- ◯ 4 years college
- ◯ 2 years college
- ◯ Other (please specify)

[ ]

2. How many years of project experience do you have?

- ◯ Less than 5 years
- ◯ 5 to 10 years
- ◯ 10 to 15 years
- ◯ More than 15 years

3. What has been your typical role in previous projects?

- ☐ Project Manager
- ☐ PMO Team Member
- ☐ Risk Management Expert
- ☐ Project Control Expert
- ☐ Project Engineer
- ☐ Educator or Trainer
- ☐ Other (please specify)

[ ]

1

4. What is the average value of your projects have worked? (X= Budget amount, m: millions)

- [ ] X < $10 m
- [ ] $10 m < X < $ 50 m
- [ ] $ 50 m < X < $ 100 m
- [ ] $ 100 m < X < $ 500 m
- [ ] X > $ 500 m

5. What type of the projects have you been involved most frequently?

- [ ] Industrial
- [ ] Housing
- [ ] Energy Sector
- [ ] Infrastructure
- [ ] Commercial
- [ ] Other (please specify)

6. In what part of the world have your projects been constructed?

- [ ] US & Canada
- [ ] Central & South America
- [ ] Europe
- [ ] Middle East
- [ ] Asia & Oceania
- [ ] Africa

Appendix B
Survey Two
EPC & PMA

* 7. Check the boxes below if you feel the engineering risk event (ERE) has a strong impact on the project management area (PMA).

Note: Resource Management Includes Management of Human, Material, Equipment and tool.

Mgt: management

	Scope Mgt	Time Mgt	Cost Mgt	Quality Mgt	Resource Mgt	Communication Mgt	Safety Mgt
Design errors or ommisions	☐	☐	☐	☐	☐	☐	☐
Misinterpretation of technical documents	☐	☐	☐	☐	☐	☐	☐
Error to update technical and project documents	☐	☐	☐	☐	☐	☐	☐
Errors and ommisions in shop drawings	☐	☐	☐	☐	☐	☐	☐
Late design decisions and drawings	☐	☐	☐	☐	☐	☐	☐
Inadequate quality planning	☐	☐	☐	☐	☐	☐	☐
Inadequate resource estimation	☐	☐	☐	☐	☐	☐	☐
Inadequate budget estimation	☐	☐	☐	☐	☐	☐	☐
Inadequate time scheduling	☐	☐	☐	☐	☐	☐	☐
Unclear scope	☐	☐	☐	☐	☐	☐	☐
Using BIM in design	☐	☐	☐	☐	☐	☐	☐
Using lesson learned in design	☐	☐	☐	☐	☐	☐	☐

Comments (please specify)

* 8. Check the boxes below if you feel the procurement risk event (PRE) has a strong impact on the project management area (PMA).

Note: Resource Management Includes Management of Human, Material, Equipment and tool.

Mgt: management

	Scope Mgt	Time Mgt	Cost Mgt	Quality Mgt	Resource Mgt	Communication Mgt	Safety Mgt
Errors in bidding process	☐	☐	☐	☐	☐	☐	☐
Selecting unskilled supplier and subcontractor	☐	☐	☐	☐	☐	☐	☐
Contract gaps	☐	☐	☐	☐	☐	☐	☐
Changing market condition	☐	☐	☐	☐	☐	☐	☐
Changing currency rate	☐	☐	☐	☐	☐	☐	☐
Lead time change (material delivery)	☐	☐	☐	☐	☐	☐	☐
Changing law or regulation	☐	☐	☐	☐	☐	☐	☐
Inadequate change management process	☐	☐	☐	☐	☐	☐	☐
Payment delay	☐	☐	☐	☐	☐	☐	☐
Availability resources of subcontractors	☐	☐	☐	☐	☐	☐	☐

Comment (please specify)

* 9. Check the boxes below if you feel the construction risk event (CRE) has a strong impact on the project management area (PMA).

Note: Resource Management Includes Management of Human, Material, Equipment and tool.

Mgt: management

	Scope Mgt	Time Mgt	Cost Mgt	Quality Mgt	Resource Mgt	Communication Mgt	Safety Mgt
Differing site condition	☐	☐	☐	☐	☐	☐	☐
Responsibility gaps between prime and subcontractors	☐	☐	☐	☐	☐	☐	☐
New user function or technology request	☐	☐	☐	☐	☐	☐	☐
Scope creep	☐	☐	☐	☐	☐	☐	☐
Delay in decision making and approval	☐	☐	☐	☐	☐	☐	☐
Contractor caused delay	☐	☐	☐	☐	☐	☐	☐
Fast tracking or crashing for accelerating time schedule	☐	☐	☐	☐	☐	☐	☐
Using wrong reference specs, codes or standards	☐	☐	☐	☐	☐	☐	☐
Inadequate resource supervising	☐	☐	☐	☐	☐	☐	☐
Unskilled employees	☐	☐	☐	☐	☐	☐	☐
Inadequate material delivery and storage	☐	☐	☐	☐	☐	☐	☐
Labor strike and union labor influence	☐	☐	☐	☐	☐	☐	☐
Owner's organization and personnel change	☐	☐	☐	☐	☐	☐	☐
Inadequate control system	☐	☐	☐	☐	☐	☐	☐
Job site security	☐	☐	☐	☐	☐	☐	☐
Construction pollution and environmental degradation	☐	☐	☐	☐	☐	☐	☐
Safety Hazards	☐	☐	☐	☐	☐	☐	☐
Unethical work practices	☐	☐	☐	☐	☐	☐	☐

Comments (please specify)

APPENDIX C - DEFINITIONS

Probability: A measure of how likely an individual risk is to occur. Also, it is known as Likelihood. PMI (2013)

Impact: A measure of the effect of a risk on one or more objectives if it occurs. Also, it is known as a consequence. PMI (2013)

Risk Breakdown Structure (RBS): A hierarchical view of risk categorizes based on specific characters. PMI (2013)

Risk Owner: A person assigned for each risk to track the risk and responses plans in the project. PMI (2013)

Probability-Impact Matrix (P-I): Used for evaluating a risk score based on a combination of each risk's impact and probability. PMI (2013)

Risk Response: Steps, actions or plans taken or to be taken to avoid or reduce the negative impact of risk events or increase their positive impact. PMI (2013)

Propagation: Scattering, spreading; reproduction, procreation, generation; transmission of an inherited trait; increase in extension; dispersion, dissemination

Risk Sources: Unexpected situations and adverse changes. Matineh et al. (2011)

Unexpected Situations: Unforeseen events (high impact but the probability of low) such as a natural catastrophe. Matineh et al. (2011)

Adverse Changes: Unfavorable alterations from the initially predicted conditions, such as a country's economic condition. Matineh et al. (2011)

Risk Consequences: effect of risk factors on project objectives, such as cost, time, quality, client satisfaction, and safety.

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ABSTRACT

PROJECT RISK PROPAGATION MODELING OF ENGINEERING, PROCUREMENT AND CONSTRUCTION

by

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The construction industry is complicated since it involves a variety of stakeholders, challenging environmental issues, huge investments, complex economic and political factors, and other features which may cause an uncertain and unpredictable environment for construction projects. Impacts of risk events can transfer from one phase (source) of a construction project to another phase (target) very quickly and can cause more damage in other phases. Thus, two surveys were conducted to understand the risk propagation phenomena among the engineering, procurement, and construction phases.

We conducted two surveys and analyzed data acquired by using sensitive analysis and binary logistic regression modeling. Risk propagation models in construction projects were developed and the interrelationship among the risk events and project management areas were established. The results indicated that “late design decisions and drawings” is

the most important risk event in terms of risk propagation to other phases of construction projects. Also, the Procurement - Construction was found to be the strongest risk event propagation relationship in construction projects. In other words, procurement risk events have the greatest impact on the construction phase. Furthermore, in this study, twenty-eight binary logistic regression models were developed among project phases and project management areas.

AUTOBIOGRAPHICAL STATEMENT

Alireza Atin graduated from Tehran's Azad University, Iran in 1997 with a B.S. degree in industrial engineering. He earned a Master of Science degree in project management from the University of Zulia, Maracaibo, Venezuela in 2012. Two years later, Alireza pursued his studies in the construction management Ph.D. degree program at Wayne State University, Detroit, MI, U.S.

Additionally, Alireza Atin has worked in several positions in construction projects and universities over the past 20 years, providing services to the clients in the construction, oil & gas, and manufacturing industries in North and South American and Middle Eastern countries. The services include (but are not limited to) the following:

- Developing integrated project management systems under PMBOK and ISO standards for some companies as a QA manager.
- Leading efforts as project control manager in program and project schedule development, Critical Path Method (CPM) analysis, WBS determination, progress reporting and Earned Value analysis.
- Managing project risk analysis efforts on complex and high profile projects and programs. Efforts included project risk planning, assessment & monitoring, quantitative and qualitative analysis, risk response planning.
- Serving as a Graduate Research Assistant, Graduate Teaching Assistant, and Research Fellow during his graduate education. Efforts included developing the guidance for risk management in international construction projects, risk and safety maturity modeling (RSMM), risk propagation modeling (RPM).