QATAR UNIVERSITY

COLLEGE OF ENGINEERING

APPLYING DECISION TREE ALGORITHMS TO DEVELOP GO/NO GO DECISION MODEL FOR OWNERS

BY

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ABSTRACT

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Title: Applying Decision Tree Algorithms to Develop GO/NO-GO Decision Model for Owner/CM/Client

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Go/No-Go execution decision is considered as the most important strategic decision for owners and project management consultants. This decision must be analyzed during the early stages of the project. Restructuring the process of decision-making may have positive results on the stability of the owner in the construction industry for longer term. The purpose of this study is to establish a proper go/no-go decision tree models for owners. The methodology of the models was developed using Exhaustive Chi-square Automatic Interaction Detector (Exhaustive CHAID) and Quick, Unbiased, Efficient Statistical Tree (QUEST) algorithms. Twenty-three go/no-go key factors were collected through extensive literature review. The go/no-go factors were listed based on their importance index as a result of a questionnaire contacted and distributed among the construction professionals. These factors were divided into four main risk categories; namely, organizational, project/technical, legal and financial/economic which are considered as inputs for models. Split-sample validation was applied for testing and measuring the accuracy of the Exhaustive CHAID and QUEST models. Moreover, Spearman's rank correlation and Analysis of variance (ANOVA) tests were employed to identify the statistical features of the received 100 responses. Through extensive comprehensive literatures of previous studies conducted,

this thesis contributes to the literature in three ways. First, it addresses the gap in literature by reviewing the current practice for conducting feasibility analysis used in construction project and studying the existing go/no-go models. Second, it provides list of decision supporting tools used in construction project and its limitation. Lastly, it is worthwhile to identify the most factors that affecting owner's decision making. Accordingly, findings from this study set out a potential set of benchmarks for companies to use when deciding the criteria to be employed to evaluate new construction project.

Another contribution is to propose a Go/No Go model which will support owner's decision in the early stage before the project commences by applying decision tree algorithms QUEST and exhaustive CHAID. The model will evaluate anticipated risk factors in the project and reduce level of uncertainty in addition to simplifying decision making for owner away from complicated mathematical method.

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CHAPTER 1: INTRODUCTION

1.1 Background

In the past several decades, construction industry has played an important role in worldwide economy. It influences and is influenced by the gross domestic product (GDP) of any nation (Okoye et al., 2016). Recently, the field has gradually broadened to be risky and complicated with its wide range of involved activities and ability to comprehend the project fully since day one. It's also riskier compared to other industries due to its complexity nature. Unfortunately, according to Nawaz et al. (2019) stated that the construction industry has poor reputation in risk classification and analysis compared to other industries.

Construction projects are frequently portrayed as perplexing and dynamic procedures that have characteristically high degrees of uncertainty. Nature of each construction project is unique and dynamic as it's involving numerous operations with multiple intricacies and varies techniques used through one single project. Moreover, numerous project stakeholders, internal and external factors involved in project life cycle which will lead to enormous risks. The many variables and complex relationships that exist in construction project made execution decision process complicated. Efficient and effective go/no go decision will give benefit for the owner or investor for future business development.

1.2 Decisions in project life cycle

There are several kinds of risk decisions making throughout the construction project starting with concept phase, planning, execution and ending with completion phase. In each phase, various stakeholders (owner, CM, contractors, consultants, suppliers, etc.) are involved in decision making upon uncertain complex process to achieve greatest value of project objectives. Project decision management is a repetitive process. The process is advantageous when is implemented in a systematic manner throughout the lifecycle of a project especially before execution phase where owner decides to go or not to go with execution. Figure 1. shows that greatest level of effort implemented is at execution phase which is considered sensitive phase to be forecasted and analyzed well to avoid losing business opportunity and consuming resources in undesirable project. However, the decision made at the very early stages will impact the project significantly.

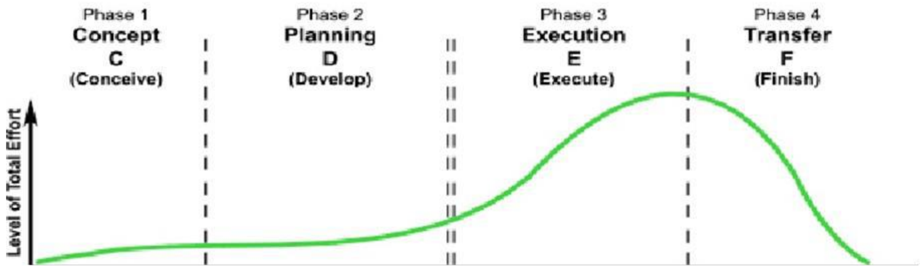

Figure 1. Life Cycle Of A Construction Project

Most of the theories of decision making in construction industry are focused on contractors' bid/no bid decision. The contribution of this study to the existing knowledge is that it introduces QUEST and exhaustive CHAID decision tree algorithms to develop go/no go models for owners. The model is supported by the attitude of the owner in relation to its competence and the risk attached to the project where the owner must evaluate risks and his capability in the planning phase before project execution. These risks play a significant role in decision making as it influences owner's profit or decision on go/no-go. The proposed model is expected to identify strategies that will meet owner's profit targets based on four main go/no go risk factors group, namely, organizational, project/technical, legal and financial/economic. The four categories consist of 23 go/no go factors. Before applying the go/no go decision tree models, owners should assess the risk level of each go/no go groups by calculating the average risk of all related factors of each group. Therefore, decision tree go/no go models should be able to predict the feasible decision in planning phase so the owner can move on to the execution phase. Decision tree models help the owner to evaluate the impacts of each go/no go factors on the project to avoid any anticipated risk.

1.3 Problem Statement

The level of investment in construction sector is expanding extremely worldwide as the case with Qatar with the announcement of award to host world cup 2022.

Underlying reasons for the existence of this problem arise from the lack of profitable projects with the challenging boundaries existing in the market. Also, most construction risk management plans are still based upon intuition, personal experience, and professional judgment, where formal techniques are rarely used due to a lack of knowledge and doubts on the suitability of these techniques for construction activities (Cretu et al., 2011). It is most likely that many of owners do not possess any practical experience or knowledge in preparing investment decisions in early stage which may result in an infeasible go decision associated with venturing into uncertain risks. A lot of researchers have been developed models supporting decisions for contractor during bidding stage such as, Kumar et al. (2019), Biruk et al. (2017) and Shi et al. (2016). However, few studies have focused on owner decision making model such as, Han and Diekman (2001) developed a go/no-go decision model using cross-impact analysis method while Chen and Yan (2017) focused on using fuzzy preference relations. Ock et al. (2005) used multi-attribute decision analysis method (MADAM) despite Won et al. (2016) used artificial neural networks (ANNs) in his model. Utama (2018) proposed Adaptive Neuro Fuzzy Inference System (ANFIS) to create his decision model. To overcome this problem, some approaches have been made to fill the gap in existing models that support decision making in planning stage for owner.

Through extensive comprehensive literatures of previous studies conducted, this thesis contributes to the literature in three ways. First, it addresses the gap in literature by reviewing the current practice for conducting feasibility analysis used in construction project and studying the existing go/no-go models. Second, it provides list of decision supporting tools used in construction project and its limitation. Lastly, it is worthwhile to identify the most factors that affecting owner's decision making. Accordingly, findings from this study set out a potential set of benchmarks for companies to use when deciding the criteria to be employed to evaluate new construction project.

Another contribution is to propose a Go/No Go model which will support owner's decision in the early stage before the project commences by applying decision tree algorithms QUEST and exhaustive CHAID. The model will evaluate anticipated risk factors in the project and reduce level of uncertainty in addition to simplifying decision making for owner away from complicated mathematical method.

1.4 Thesis Objectives

In view of this challenge, the primary objective of this study is to develop sophisticated methods to:

1. Identify, explore, and rank major relative construction risk factors for owner's Go/No Go decision using relative importance index and categorize these factors into related influence group.

2. Develop QUEST and exhaustive CHAID decision tree for Go/No Go models for owners as a decision tool in the early stage before execution.
3. Develop statistical analysis for: 1) decision tree models; 2) respondents; 3) Go/No Go factors.
4. Provide recommendations to owner for practical use of the model.

Decision trees based on QUEST and exhaustive CHAID growing methods will be used to develop go/no go models for owners or even project management consultants. Owners will evaluate the average risk of each go/ no go group independently, then apply the result in the decision tree model to have a go / no go decision at the early stage before the project execution. The 23 go/no go factors were compiled as outcomes of extensive literature review.

1.5 Thesis Outline

In general, this paper is structured into the following five chapter:

Chapter 1: This chapter includes background about construction project risks, problem statement and thesis objective.

Chapter 2: This chapter shows the literature review that has been performed on existing feasibility evaluation for project and go/no-go models in the construction industry, and it also gives brief explanations about each model.

Chapter 3: This chapter represents the methodology approach of this research study and introduction of data mining, classification & regression concept, decision tree concept, decision tree algorithms (QUEST & exhaustive CHAID). Moreover, it includes the concept of developing a go/no-go decision model for owners and shows all steps and all baseline of this study such as: demonstrating the population and sample size, designing steps of questionnaires and providing brief justifications about the statistical tools used for this study.

Chapter 4: This chapter demonstrates all the data analysis including: descriptive statistics of respondents (experience, company sector, company work volume, ranks of the factors affecting the go/ no go decision, One- Way ANOVA test amongst respondents, decision tree models based on QUEST and exhaustive CHAID growing method and models validation (split-sample validation). It also demonstrates the go/no-go decision tree models for owners, investors and project management consultants.

Chapter 5: This chapter includes the conclusion and some recommendations as an overall out of this thesis. It also provides the contribution of the study and recommendations for future work.

Following the main text, this thesis also includes two appendices. Appendix A presents a sample of the questionnaire used throughout the interviews. Appendix B includes multiple comparison tables.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter includes the literature review of the practice for conducting feasibility analysis used in construction project, existing go/no-go models and brief explanations about each model. Moreover, decision supporting tools used in construction project and the limitation and challenges of each proposed model were added at the end of each paragraph. Lastly, review of the most factors that affecting owner's decision making. Overall, the literature will be based on the following questions:

- What was done? (feasibility analysis used in construction project, existing go/no-go models)
- How it was done? (decision supporting tools used in construction project)
- What kind of factors affect the decision making?

According to Bennett (2003), in his book he divided the project life cycle into six phases: Pre-project phase, Planning and design phase, Contractor selection phase, Project mobilization phase, Project operations phase and lastly Project closeout and termination phase as presented in Figure 2. This section focused on a review of recent literature limited to decision making during early stages after conceptual design phase.

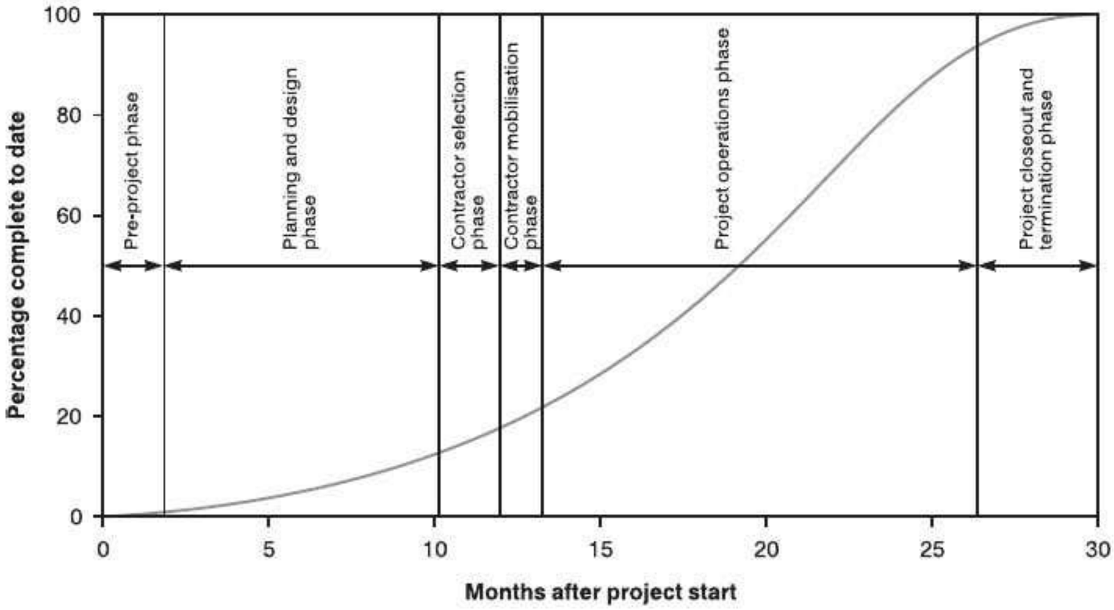

Figure 2. Typical construction project life cycle

2.2 Previous literature on feasibility analysis

This section presents a review of recent literature on project feasibility study in early stage:

One of the first examples of feasibility analysis used in construction project is presented in Firmansyah et al. (2006). The study discussed the importance of conducting project feasibility before starting the investment in order to eliminate any uncertain future risk and achieve higher benefits. Risk variables were classified into eight groups with total 53 factors that influence the successfulness of project. The researcher used two analysis, risk probability matrix to classify risks from highest to lowest using ranking in order to give treatment for highest risk first. Second analysis is financial analysis used to examine each parameter values previously identified to know whether the investment is feasible or not and compare it to one of investment judgment tools (ROR, NPV...). The researchers also used sensitivity analysis to establish relation between calculation in investment parameters values and feasibility study to show the impact of changing. The researchers concluded that risk factors extremely influencing investor's decision specifically economic factors due to its high sensitivity.

A recent study by Chillingworth (2015) developed a pre-project feasibility tool and methodology that effectively engage and support project stakeholder's decision according to their expected outcomes. The researcher established feasibility formula as effective tools in identifying to what extent the project match owner/project manager organization goals, probability of project successfulness and key factors affecting decision making before launching the project. Feasibility formula spreadsheet consists of eleven elements (Strategic Alignment, Risk, Financial, Stakeholder Satisfaction, Human Resources, Political, Brand, Organizational Maturity, Policy or Strategic Benefits, Compliance and Ethics). The owner/CM need to identify his objective for each element then rate its importance on scale from 1- 10 based on his organization perspective. Following that, is to score the identified project's ability to satisfy these objectives, through complex calculations developed by excel software will transpose entered data into final dashboard that will result percentage decision which will assess the stakeholders whether to proceed with the project or stop it. The research concluded that despite variations in owners/organization objectives, his model appeared generalizable in terms of relevance and value. Researcher aimed achieved by providing new contribution in the form of new decision-making tools that facilitate decision maker through the identification of an organization's strategy and objectives.

Elhassan et al. (2012) reviewed the optimization techniques used to improve decision making in construction sector. The researcher focused in reviewing the use of artificial intelligence algorithms (AIA) in optimization models relevance to construction decision making. AIA concept adopted human brain intelligence to solve multi objectives optimization problems. It includes genetic algorithms, fuzzy logic, artificial neural network and ant colony optimization. Through sixteen previous research papers, the author summarize AIA applications and found they are promoting using AIA with time constraint or time and cost tradeoff constraints or some combinations of quality, cost, time and environmental impacts while there are many combinations of constraints can be considered. For example, risk constrains that affect decision making process.

Jónsson (2012) studied the current practice for performing feasibility analysis for construction project during the conception phase focused in Iceland. The researcher aimed to determine the main factors to be considered during the process of feasibility analysis prior the starting of the project. Also, highlighting which procedures can be classified as best practice for conducting project feasibility study. The author prepared comprehensive overview of the methodology used for conducting feasibility study subjected to descriptive cases and found that the framework consists of six processes, project overview, alternatives, benefits and cost, net present value (NPV), sensitivity analysis and finally making recommendation. The researcher conclude that the current feasibility analysis procedures performed during the concept phase founded lack of consistency in procedure and varies from project to another.

Kim et al. (2005) introduced decision programming language (DPL) and CRYSTAL BALL feasibility method based on systematic approach to be used by decision maker/investors in risk management. The proposed simulation model expected to reduce the risk complexities and competitive construction environments supporting initial decision.

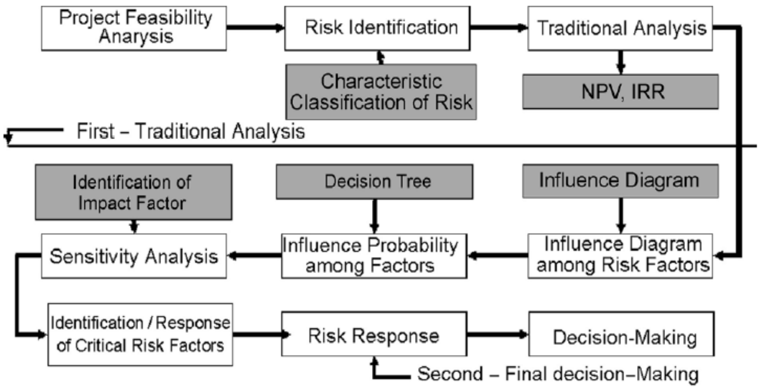

Figure 3. Project Feasibility Analysis Model

According to Figure 3, the first step was identifying the potential risk factors that can be occurred then classifying them into main groups subjected to their characteristics risk (Finance, construction, legal and Market). Following that, the author used influence diagram and decision tree to catch the relevance and importance of all risk factors. Last step was carrying sensitivity analysis using Monte Carlo simulation method to determine the critical factors and how it can be solved. The researcher conclude that profitability part is the most important part in stage of project planning and feasibility analysis, thus financial risk considered the most critical risk factors. Accordingly, the decision maker sets "project profitability" as an absolute goal to be considered for decision criteria subjected to an identified scale in order to go or no go with project.

2.3 Previous Go/No-Go Models

The go/no go technique issue had been focal point of research since the mid-1950s. The principal models found in the writing be that it decreased the issue of go/no go choices to the construction of anticipated estimation of benefit and computation of winning probabilities. The numerous properties' classification incorporates the models that utilize the assessment of different variables as the premise to help the owners in their decision.

Taylor et al. (2000) have reported risk-based model to support go/no-go decision making in construction sector in United Kingdom. Risk management within the UK construction sector is essential. Therefore, assessment of investment risk is essential using stochastic risk simulation to predict risk behavior and predict uncertainty faced by the UK contractors. This model helps in calculating the financial risks and modelling them using Monte Carlo sampling techniques.

Han and Diekman (2001) developed a go/no-go decision model using cross-impact analysis method. This method had been developed to predict forthcoming events through the evaluation of the connections found among the variables. Through this technique, the initial probability is defined and the interconnectedness between the variables are revealed through the help of “cross impact relationships” (Han and Diekman, 2001). This model comprised of 32 variables as seen in Figure 4.

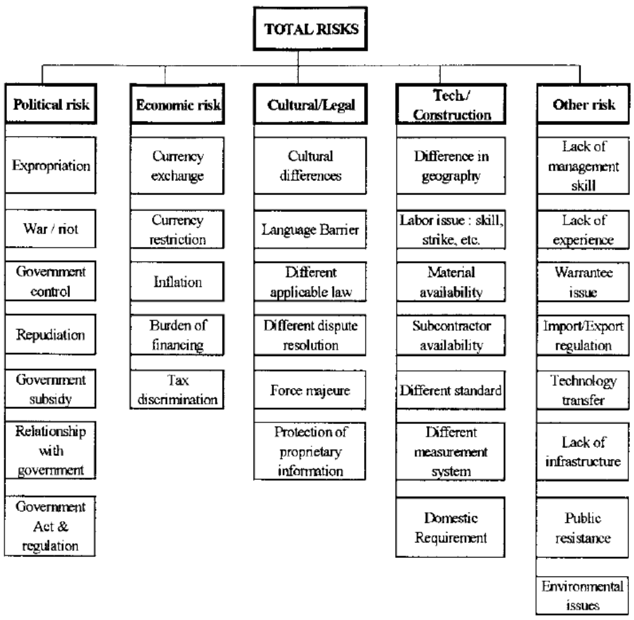

Figure 4. Breakdown Structure Of Risks

The variables have been classified into different groups, which are discussed as follows:

1. **Country Conditions:** Country condition deals with the country's environment and uniqueness in conducting trade. It includes the following variables: cultural and legal conditions, political conditions, geographic and climatic conditions, environmental conditions, and economic conditions (Han and Diekman, 2001).
2. **Contractor's Decision Strategy:** This is considered to be another group in the CIA based go/no-go model, which comprises of the following variables: resources, owner relationships, strategic partnerships, skills, and experience. Variables under this group are known to be controllable.
3. **Intermediate Variables:** The third group is the intermediate variables, which are divided into two categories: controllable and uncontrollable. The former is influenced by "contractor decision strategies", whereas the latter deals with variables that are beyond human control (Han and Diekman, 2001).
4. **Successor Variable Set:** The fourth group comprises of variables that deals with the project success. The variables in this group include project schedule uncertainty, project cost uncertainty, and contactor's competency in terms of project management.
5. **Outcome Variables:** The last set of variables deals with profitability of the project and other benefits, which are used to take the go/no-go decision.

The researchers tested the model and concluded that the model is effective in defining conditional relationships that are subjective in nature and can also describe the values of the outcomes that demonstrate unclear associations between the variables. The researchers also asserted that can be used by the decision-makers to predict the project's profitability and benefits through the usage of different go strategies combinations. They also concluded that this method is subjective in nature and therefore, it can help experts to express their opinions based on their subjective knowledge, which is the fundamental requirement of the model. Finally, the researchers suggested that the model is essential in terms of supporting the prediction of future events by evaluating different variables under different decision options.

Ock et al. (2005) developed and proposed a go/no-go model for build-operate-transfer projects (BOT). The researchers assert that the success of the BOT projects is dependent on the promotion of the appropriate project. However, the selection of the project is based on the early project start procedures. In order to pursue the project before its inception, clients focus on expert advice, judgement, and intuition to understand the complex nature of BOT projects. According to Ock et al. (2005) BOT projects success is dependent on six essential factors: the right ownership and entrepreneurship, selection of the correct project, strong project team, strong and effective technical solutions that are practically feasible, financial proposals that are financially viable, and competency to manage such the project. Consequently, BOT project development requires strong and effective project management solutions during its early stage to ensure that they are not affected by the parameters of cost, quality, and time.

As a variety of risks are present in such projects, which can affect the occurrence of risks, Ock et al. (2005) focused on proposing go/no-go decision model for BOT projects. The researchers aimed at creating a model that aimed at using multi-attribute decision analysis method (MADAM) to validate the go/no-go decisions for BOT projects and to use it during the early stage of the project development process. The go/no-go decision model has two parts: decision process model and a decision variables relationship model. The former is based on making go/no-go decisions under uncertain conditions through the use of logical sequential decision making (Ock et al., 2005). The latter focuses on identifying the project features based on computer modelling, which helps in identifying the risks and decision attributes, depicting their complex structure, which is hierarchal in nature.

The decision process model is responsible for identifying two types of risk variables: negotiable risk variables and non-negotiable risk variables. Both variables are differentiated from one another. Risk variables are known to be the factors that require probability and stochastically analysis to identify their effect on other decision features and risk variables. Decision attributes have been identified as the variables that comprise of the utility scores, which are used for the estimation of project viability. This model influences the decision-makers to ensure that the attribute has a specific acceptance level. It aids the go/no-go decision making based on the creating of strategic substitutes for improving the overall project conditions and calls for the collaboration with different stakeholders.

The second procedure of this model is related to the decision variables relationship model. In this step, modeling procedures are adopted to create the model. There are two types of modelling procedures used. The first focuses on differentiating the decision variables and their associations with the help of influence diagrams. The second procedure focuses on creating a hierarchal structure that shows the overall variables and their relationship. According to Ock et al. (2005) influence diagrams to differentiate between the decision models and their relationships is achieved. The authors identified 20 decision variables to be included in their go/no-go decision model, which were identified with the help of case studies. By creating the influence diagram of different variables, the relationships are then moved to hierarchal linear relationship to understand the complex model. In this category, project feasibility is evaluated by identifying the decision attributes. 10 risk variables have been classified and are expressed as “good–bad or excellent–moderate–bad, depending on the model user’s judgment as to their appropriateness to addressing the project conditions signified by the variable” (Ock et al., 2005). The researchers had tested the model and concluded MADAM go/no-go decision model is instrumental in improving the decision-making process for BOT projects during the early stage of project.

Won et al. (2016) asserts that several construction companies over the years have focused on expanding their business operations in foreign markets. However, many of the companies have experienced issues and difficulties in keeping up with the international construction market because of intense competition and most primarily, because of lack of knowledge of their own core competencies and the risks associated with international projects. For this purpose, Won et al. (2016) developed a go/no-go decision model that focused on construction firm’s core competencies, risks associated with the project, and the business philosophy of the organization. In order to create the model, the researchers conducted and classified it into two main stages. The first stage comprises of evaluation models: project risk assessment model and corporate core competency models. Through the use of artificial neural networks (ANNs), these models were created based on the data collected through the survey. In the second stage, fuzzy logic model had been incorporated to support the go/no-go decision. The authors assert that the models have two essential input values of linguistic significance; the former is the net competency value and the latter is competency factors. Net competency value is dependent on the risk score, whereas the competency factors deal with the corporate’s method of doing business. The researchers concluded that this model could help companies with go/no-go decision, enabling them to take the project based on their core competencies and business philosophy.

Chen and Yan (2017) study focused on developing go/no-go decision model to help Chinese investors in making decision to invest in PPP project by using fuzzy preference relations. The authors divided the factors in four categories, which were:

1. Governmental related factors
2. Project related factors
3. Environmental factors
4. Investor related factors

On basis of the factors identified and the utilization of fuzzy preference relations (FPR) method, the researchers devised a model for go/no-go decision in terms of making investment in China. The authors assert that this model can be utilized to aid such decisions during the initial stage of the project by considering the risk score associated with the factors identified. The model is different from its predecessors as it is objective in nature and because previous models are influenced by subjective data. Based on their analysis, the researchers concluded that this model can be beneficial in improving the overall efficiency of the investment decision making. However, the authors also concluded that the study cannot be validate the applications of the model as the changes caused by PPP project progress have not been considered.

Utama (2018) created a go/no-go model based on the use of Adaptive Neuro Fuzzy Inference System (ANFIS) to provide decision support for overseas construction project in terms of go/no-go decisions. A variety of factors had been identified by the researcher through extensive research. The international variables identified were:

1. **Project Attributes:** Project attributes include variables project size, complex nature of the project, level of competition, site condition, type of project, and project location.
2. **Contractors:** This includes different variables such as types of contract, quality and clarity in contracts, and the duration of the contract.

3. **Client Score:** This include the type of client and the reputation of the client.
4. **Host country:** The variables included in this domain are political stability, legal environment, cultural environment, economic stability and condition, and ease and friendliness to do foreign business.
5. **Business:** This includes local resources availability, market significance, familiarity with the host country, financial ability and competence, and cost associated with conducting business.

Based on these variables, ANFIS is used to evaluate the project in order to support go/no-go decisions. The author employed several techniques to test the performance of ANFIS model by using root mean square error (RMSE) and coefficient of correlation (R) to validate his proposed model. The researcher concluded that, developed ANFIS model evidence that it can be a satisfactorily predictable decision tools for helping companies' decision maker in project preliminary assessment.

2.4 Go/No-Go decision Models in Other Sectors

In project management, go/no-go decision criteria are essential. Many of researchers have agreed the significance of well-defined and well-structures decision based on the needs and requirements of the project. According to Isa et al. (2014), go/no-go model is responsible to allows organizations to exercise responsibility and provide a supportive organizational culture, which focuses on information exchange, improving communication among various stakeholders to aid the decision-making process. Conventionally, within the project management domain, go/no-go model focuses on identifying alternates, which can affect the decision-making process. As indicated in literature, project management is based on project management activities that require strong and critical decisions based on go/no-go models, which fortify the entire process. It should be noted that the use of go/no-go models is not limited to construction sector. This decision criteria have been modelled in other sectors as well. These sectors include pharmaceutical sector, medicine, information and technology.

Chuang-Stein et al. (2011) conducted a study to create a go/no-go decision model in new drug development. The research model is based on probabilistic analysis that helps in aiding the go/no-go decision-making process in the development of the new drug.

Vernon and Johnson (2005) have reported the use of go/no-go decision-making criteria in the development of new pharmaceutical products during the early stage of its development. The researchers modelled their go/no-go decision model using mathematical modelling techniques. The model is responsible for predicting the future prices of the product by considering variables such as cost effectiveness. Using stochastic assumptions, simulations and analytic methods had been employed to support the decision-making criteria. Based on the results, the researchers concluded that this go/no-go model can help in reducing the overhead costs in product development and can reduce the risks associated with in-licensing during the early stage of the product development.

Sadoff and Hone (2005) had developed a go/no-go decision model for the development of tuberculosis (TB) vaccine. The researchers assert that go/no-go decision is essential to improve the vaccine development during its early stages to ensure that the program is successful. Development of new products require research, costs, and manpower that accelerates as the project develops. Bad vaccine projects can result in wastage of resources.

The essential components identified for the go/no-go decision-making development of TB vaccine are discussed as follows:

1. **Safety Considerations:** Safety consideration is essential to support go/no-go decision during the early development of the vaccine. The vaccine needs to be safe for the humans and therefore, mandatory clinical trials are essential for its testing.
2. **Technical Considerations:** Variables such as manufacturing, process, stability, release and validation are essential before releasing it to the market.
3. **Net Present Value:** This variable focuses on calculating the resources required to develop the vaccine.
4. **Other Variables:** Other variables that need to under consideration include intellectual property rights, human safety, human tolerability, animal safety, animal toxicology, event profiles in adverse conditions, and human immunogenicity.

Lin and Chen (2004) have explored the possibility of using go/no-go decision criteria by modelling it with the help of fuzzy linguistic approach. New product development considered to be critical activity which can affect the overall processes. Therefore, screening of the new concept is essential. However, it is suggested that the screening is not sufficiently performed. New product development is affected by the parameters of time and nature. In order to support the screening of new product development (NPD), go/no-go decision model had been proposed by the researchers to support the screening process during the initial stages of NPD. Project evaluation and selection criteria considered by the researchers is based on the following: product attributes and characteristics, competitive advantage marketing, technological relevance and risks associated with the product using fuzzy logic. Measurements identified had been defined in linguistic terms. Success attributes had been identified based on the fuzzy values determined. The following variables have been considered within the criteria factors:

1. **Competitive marketing**: Variables in this domain include market timing, product price, marketing abilities and capabilities, and market attractiveness.
2. **Product superiority:** This include functional variables and unique attributes that makes the product attractive.
3. **Technology appropriateness:** This include uniqueness of design, the use of high-quality materials, manufacturing capacity of the firm, and supplying to different suppliers.
4. **Risks:** This includes risks associated with market competition, technological uncertainty, and financial risks.

Each of these variables are analyzed through the use of fuzzy numbers and are evaluated based on their weightage. Based on the results obtained, the researchers concluded that this model can be used effectively for go/no-go decision in NPD.

The potential of go/no-go decision making has also been investigated by Ba et al. (2016), who used it to investigate the risky driving behavior of drivers using go/no-go simulator driving task. A total of eighty-four participants were part of the study. The simulation model had been developed by using Driving Behavior Questionnaire and Balloon Analogue Risk Tasks. Based on the data collected, they concluded that high-risk drivers were most likely to violate traffic rules and therefore, were prone to making violations.

2.5 Decision tools used in construction project (Bid/no-bid Models)

There is no doubt that the lack of previous strategical models that providing the owner a future prediction for project successfulness are limited and not used as actual practice in early stage rather than for academic purpose. However, this part will review previous decision models used in bidding phase by contractor and study how relevant these models to owner decisions in early stage prior final Go decision. Due to extensive previous competitive researches in bid/no bid models that have been introduced, the researcher aimed to review the recent studies in this topic and employ new techniques to develop Go/No-Go decision in early stage for owner. The literature will review bid/no-bid models conducted during the period between 1990 and 2019 as following:

One of the first examples of previous model is presented in Eldukair (1990) study who developed systematic model based on fuzzy set theory and multi-criteria modeling to help the contractor in bidding stage. He identified four main group that influencing contractors bidding decision as following: bid price, nature of project, resource capability and performance. In this methodology, the expert is evaluating the proposed project with respect to certain identified desirable goals. Eldukair employed fuzzy functions and operations to rate and the relative importance of the criteria required to evaluate the available projects for bidding. Then, he established mathematical relation between the relative importance of criteria and score of projects to calculate the total effect of the criteria. The ranking measure can be calculated by dividing the fuzzy weighted average for each project alternative by the overall impact of the criteria. The last step in this approach is to calculate the expected value measure, the project alternative with the highest expected value measure is considered as the favorable bidding strategy.

Ahmad (1990) proposed a structured methodology for evaluating bids decision. The researcher developed Objectives-Attributes Hierarchy for Bid/No-Bid Decision Problem based on the overall worth-assessment technique. A set of identified important factors with combination of relative weight for each factor to calculate the acceptance level of project worthiness. These factors are divided into four hierarchical groups, job, firm, market, recourse category including total 13 bidding factors determined through questionnaire survey conducted from 400 contractors in the United States. The author decomposed the process of bidding decision making into two phases, deterministic followed by a probabilistic one. The first phase reveals certain importance factors affecting bid/ no bid decision such as project location, project type, while the second phase deals with uncertain criteria, expected risk, competition level. The deterministic stage based on mathematical calculation for the total worth obtained for certain project. Its summation of multiplication of worth scores by worth weight. Worth scores of each factor assigned by decision maker with range from 0 to 100 while worth weight is calculated by pairwise comparison. The last step is to compare overall worth with threshold worth by calculating the difference resulting desirability strength score which will reflect the strength of the decision to bid. The bid considered unworthy if the score close to zero and worthy if it's close to ten. The inputs of the model are intensive.

M. Wanous et al. (2000) focused on adopting a parametric approach in terms of bid/no-bid cases. For this purpose, the authors consulted the work of previous researchers, Wanous, M., Boussabaine, A.H. and Lewis (1998), and identified 38 factors. The researchers adopted 18 factors and discarded the remaining as the importance index scores for the formers were higher than 50%. 13 of the factors were classified as positive factors, while, the remaining were classified as negative factors. For each of the factor, a threshold value is determined. Each value can be positive or negative. The assessment of the 18 factors on the scale of 0 to 6 needs to be assessed by the decision makers. The bidding index is then created and represented mathematically using the parameters: contractors' evaluation of the situation, positive factors, negative factors, and importance indexes. When the bidding index exceeds the value of zero, the bid decision goes forward. Otherwise it is not. The researchers had been successful in developing a model using artificial neural networks (ANN). The network comprises of an input that had 18 input nodes based on the positive and negative factors, two layers that are hidden, and one node for getting the output. Using the questionnaire that was distributed among the Syrian contractors, the model had been validated (Mohammed Wanous et al., 2003).

Lowe and Parvar (2004) developed a bid/no- based model, using historical data from a UK based company by employing logistic regression approach. The data had been utilized to study the factors that influenced the decision to bid on projects. Based on the factors identified, a model had been proposed by the researchers. Through use of correlation techniques, factors that were significant were identified. Out of 21 factors, only 8 factors were significant in terms of having a linear relationship with decision to bid. 1 has been identified to move ahead with the bidding, whereas 0 had been identified for rejecting the project.

In 2004, Lin and Chen published paper in which they introduced fuzzy linguistic method to assist contractors in bidding decision problems. This approach concentrates on the application of linguistic approximation and develops fuzzy arithmetic to evaluate bid/no-bid decision. The approach can be explained step wise as following: First step, establishing target criteria for assessment based on organization requirements then conducting the survey bid opportunity related information. Second step, determining the scale for measuring the importance weights then measure the screening criteria rating and weight using linguistic terms that will be approximated later by fuzzy number. Last step, these fuzzy numbers are aggregated to obtain a fuzzy attractiveness rating that will be matched with appropriate linguistic levels identified by managers previously. The bid with the higher attractiveness is encouraged the bid decision to be made.

El-Mashaleh (2010) had been successful in the development of a non-parametric linear model through data envelopment analysis (DEA) approach to resolve bid/no-bid decision problems. For this purpose, 10 factors had been identified: five factors were negative bidding factors and five positive bidding factors. Based on subjective data, these factors had been identified to help contractors in the bidding decision process. DEA had been used and identified as a method of labelling and identifying bidding opportunities that were promising. Based on the nature of the bidding opportunities, the bid decision had been undertaken. If the bidding opportunity exhibited to be promising, the bid decision would be undertaken. However, it was not promising, the decision would be negative.

The same researcher developed an empirical framework to support the bid/no-bid decision making (El-Mashaleh, 2013). The new model had two components that were deemed to be successive: critically bidding factors and relative importance index. DEA analysis had been incorporated in order to determine their relative importance. A total of 53 factors were identified, out of which only 20 factors were considered because of their highest relative importance index values. The remaining factors were not considered. The researcher categorized 5 factors and 16 factors as input and output respectively. For all variables, the efficiency rating had bene calculated. If the efficiency score was greater than 1, bid decision would be taken. If the score was less, it would not be proceeded with.

Shi et al. (2016) developed a novel model by using a rough set (RS), and general regression neural network (GRNN), based on niche particle swarm optimization (NPSO) algorithm for bid/no-bid decision making. GRNN network structure is composed into four main layers, inputs layers, a pattern layer, a summation layer and the output layer. The researcher identified 22 variables influencing bid making based on previous literature and then he modified them into five main categories as following, resources, company's reputation, company's mission, risk of project and competition of project. In this paper, rough set theory used to find the optimal reduction among these variables resulting eight variables having major impact on decision where they used as inputs of NPSO-GRNN model while tender decision is the output. By developed mathematical software for prediction, the bid decision conducted. Using the Mean Absolute Percentage Error, the model has been measured in terms of prediction accuracy.

Biruk et al. (2017) put forwards a parametric approach, combination of using multi-criteria analysis method and linear programming model for assessing desirability of potential bid that support managerial decision based on calculating the total bid price. The researcher utilizes the total bid price as function of bid desirability with weighting score on scale from 0 to 1 assigned by expert evaluation. By means of AHP and pair-wise comparison were used to calculate the criteria weights by the same expert. The technique used the simple additive weighting to calculate the total project desirability score. The minimum acceptance for bid should be not less than 0.5, otherwise no-bid decision is made.

Kumar et al. (2019) recently published paper on key factors influencing bid decision model through a structured questionnaire survey among different top contractors. The researchers ranked these factors with a score from 0 to 6 according to its importance level and develop a non-parametric approach using Data Envelopment Analysis (DEA) model which is a linear programming methodology to measure the efficiency of multiple decision-making. Developed model generates favorability score for each bid opportunity resulting efficiency value which is compared to cut off value. Consequently, if efficiency value of certain bid is higher than cut-off value, the bid decision considered favorable and contractor is advised to bid for this project.

2.6 Review of factors affect the owner decision making:

Numerous researchers and studies have been contributed to defining the go decision attributes in construction industry. Literature on go / no-go decision factors was performed to identify the key factors that influence decision maker's judgment. Extensive studies by (Bahamid et al. (2019), Abd-Eltawab (2018), El-Karim et al. (2015), Yucelgazi and Yitmen (2019), Amoatey et al. (2015), Bagaya and Song (2016), Sharaf and Abdelwahab (2015), Issa et al. (2015), Zidane and Andersen (2018), Kishan (2014), Asadi and Rao (2018), Singh et al. (2017), Al-Hazim et al. (2017), Sharafi et al. (2018), Bageis and Fortune (2009), Hwang and Kim (2016), Jarkas et al. (2014), Zou et al. (2014), Kadry et al. (2017), Horine (2009), Diab et al. (2012), Gavit et al. (2019), Kishan (2014), Sakthiganesh et al. (2017), Gondia et al. (2020), Bahamid et al. (2019), Dai et al. (2016), Jang et al. (2015), Jang et al. (2015), Asadi and Rao (2018), Shankar (2015), Wu et al. (2017), Mishra and Mallik (2017), Amoatey et al. (2015), Hastak and Shaked (2000), Chua et al. (2003), Firmansyah et al. (2006)) have identified the most influencing factors affecting go/ no go decision. In this study, a draft questionnaire of 23 key risk factors prepared from literature and distributed into four main group (Organizational, Project/Technical, Legal and Financial and Economic).

Content validity evaluated by three experts in order to check readability, offensiveness of the language and to add more factors and information if needed. Table 1 demonstrates the top twenty-three go/no go decision attributes with their corresponding literature references.

Table 1. List Of 23 Risk Factors With Their Corresponding Literature References

Organizational Risk Factors (Owner/Client, CM, designer, planner, contractor.)	
1. Financial stability of Owner/Client	Bahamid et al (2019), Abd-Eltawab (2018), El-Karim et al (2015), Yucelgazi and Yitmen (2019), Amoatey et al. (2015), Bagaya and Song (2016)
2. Consultant, Suppliers reliability and experience in construction	Sharaf and Abdelwahab (2015), El-Karim et al (2015), Yucelgazi and Yitmen (2019), Issa et al (2015), Zidane and Andersen (2018)
3. Design Errors and Omissions (Rush design)	Kishan (2014), Asadi and Rao (2018), Singh et al (2017), Yucelgazi and Yitmen (2019), Al-Hazim et al. (2017), Zidane and Andersen (2018), Sharafi et al (2018)
4. Qualification of Designers & planner	Bageis and Fortune (2009), Hwang and Kim (2016), Jarkas et al (2014), Zou et al (2014), Yucelgazi and Yitmen (2019), Zidane and Andersen (2018)
5. Availability of skilled and unskilled workers / labors	Zou et al (2014), Singh et al (2017), Yucelgazi and Yitmen (2019), Kadry et al. (2017), Zidane and Andersen (2018), Sharafi et al (2018)
6. Availability of reliable and experience contractors	Horine (2009), Sharaf and Abdelwahab (2015), Zou et al (2014), Yucelgazi and Yitmen (2019), Kadry et al. (2017), Bagaya and Song (2016)
Project/Technical Risk Factors	
1. Availability (materials & equipment)	Diab et al (2012), Sharaf and Abdelwahab (2015), Singh et al (2017), Gavit et al (2019), Bagaya and Song (2016)
2. Erroneous geological condition study	Kishan (2014), Sakthiganesh et al (2017), Gondia et al. (2020)
3. Availability of construction technologies / and skills	Bahamid et al (2019), Yucelgazi and Yitmen (2019), Bagaya and Song (2016), Dai et al (2016)
4. Size and location of project	Jang et al (2015), Asadi and Rao (2018), Sharafi et al (2018)
5. Safety level required	Shankar (2015), Yucelgazi and Yitmen (2019), Issa et al (2015), Sharafi et al (2018)
6. Clarity or Complexity of the design and scope	Bahamid et al (2019), Yucelgazi and Yitmen (2019), Issa et al (2015), Dai et al (2016)
7. Site space constraints	El-Karim et al (2015), Gondia et al. (2020), Sharafi et al (2018)
8. Tight schedule	Abd-Eltawab (2018), Asadi and Rao (2018), Zou et al (2014), Issa et al (2015), Wu et al. (2017), Al-Hazim et al. (2017)

Legal Risk Factors	
1. Excessive approval procedures in administrative government departments	Zou et al (2014), Abd-Eltawab (2018), Gavit et al (2019), Gondia et al. (2020)
2. Country specifications and standards level in regulations and permits	Bahamid et al (2019), El-Karim et al (2015), Gondia et al. (2020)
3. Lack of legality and standard dispute settlement procedure	Bahamid et al (2019), Asadi and Rao (2018), Liu et al. (2016), Gondia et al. (2020), Dai et al (2016)
Financial and Economic Risk Factors	
1. Underestimated budgeting	Zou et al (2014), Abd-Eltawab (2018), Mishra and Mallik (2017)
2. Inflation and deflation	Kishan (2014), Sakthiganesh et al (2017), Shankar (2015), Yucelgazi and Yitmen (2019), Amoatey et al. (2015)
3. Price escalation of raw materials	Yucelgazi and Yitmen (2019), Issa et al (2015), Liu et al. (2016), Amoatey et al. (2015)
4. Expected return level/Project profitability	Mishra and Mallik (2017), Hastak and Shaked (2000), Chua et al (2003)
5. High overhead cost.	Mishra and Mallik (2017), Firmansyah et al (2006)
6. Forecast about market demand / Potential level of competition	Mishra and Mallik (2017), Sakthiganesh et al (2017), Dai et al (2016)

2.7 Conclusion

The purpose of this literature review was aimed to find out the methodology of previous feasibility studies used in construction sector in early stages that used by decision maker, also exploring the existing go/no-go decision models in different sectors and how it was employed according to the desired decision purpose. Moreover, reviewing the viability of assessment models used in bid/no-bid decision stage to find out all the ways used in decision making by different stakeholders in order to reach the aim of this paper and develop professional practical alternative concept to solve decision problem. Consequently, higher achievable and successful project will be delivered.

From the previous studies that has been reviewed, it can be concluded that a considerable amount of literature has been published on contractor decisions while there has been relatively little literature published on owner/ clients or construction management firm decision. Also, certain models required complicated inputs and advanced understanding of mathematics and required software to run the model, which is not practical for the owner. Additionally, some models didn't address the importance of risk assessment in early stage of the project while focusing on bidding stage despite that early stage decision is much critical decision to be considered. Moreover, some previous feasibility models exclude some factors affecting owner's decision and mainly focusing in financial factors, a combination of all expected factors will result better decision strategy for owners. Thus, the researcher found out that developing a practical, easy and fast model that support owner's decision in early stage of the project is significantly needed.

2.8 Proposed Model support Go/No-Go Decision

Decision tree models is a tool which, the owner can use it easily with graphs and colors, it aids the owner to determine the source of the risk. Decision tree model draws a tree diagram with roots node and branches that can be easy to figure out the final decision and the level of the risk. With this thesis, a decision tree based on exhaustive CAHID and QUEST is firstly introduced for go/no go decision model for owner in the construction sector. The decision tree displays the soft spots and hot spots between the independent and dependent variables, which, leads to a better decision. Decision tree models display the result effectively in visual terms, easy to understand and easy to apply. To the researcher's knowledge, this is the first study in the literature introducing exhaustive CHAID and QUEST decision tree model for go/no go decisions in construction firm.

CHAPTER 3: METHODOLOGY

3.1 Introduction

The aim of this chapter is to explain the research process in achieving research objectives. Its represents the following: methodology approach of developing go/no-go decision tree models based on exhaustive CHAID and QUEST algorithms, justification of the population and sample size, questionnaire structure and the statistical tools, which were used to investigate and validate the go/no-go decision model and to extract importance features of the respondents.

3.2 Data Mining

Data mining can be defined as powerful predictive tool of observed data or data from warehouse with special algorithms that aimed to discover certain hidden pattern and form it in a novel way to be useful Pallavi (2016). Also, it's a technique to find relationships across unrelated data to extract the hidden predictive or behavior that can support decision making. Data mining helps decision maker to optimize their decision value and level of exposure risk proportional to premiums earned.

Generally, according to Pallavi (2016), stated that most of successful business decision are based from reliable date and their validation through data mining techniques. Therefore, many researchers have been focused on developing decision support systems by understanding the business case and convert the archived historical data using special algorithms to generate decision prediction model.

Knowledge discovery in Database or KDD is another synonym of data mining, many researchers treat the data mining as a fundamental step in the process of discovering knowledge from a random database (Han et al., 2011). The figure below illustrates the taxonomy of the data mining methods, each approach has its own algorithms and methodology (Rokach and Maimo, 2014).

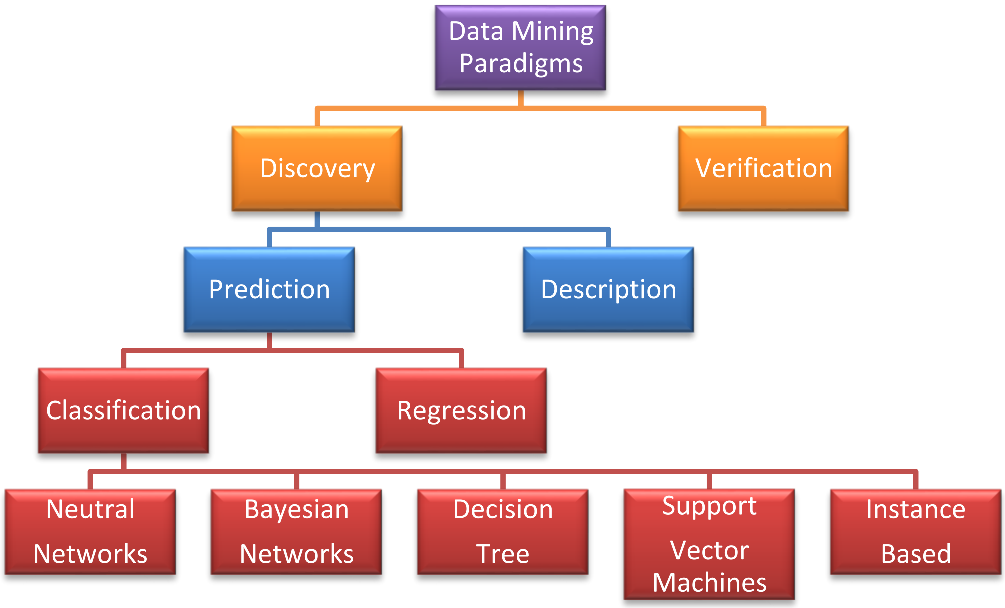

Figure 5. Taxonomy Of Data Mining Methods

The main purpose of these techniques is either prediction or description. Both types of the study are represented by the knowledge discovery by using data viewing tools for description part while using fundamental statistical analysis for prediction part.

3.3 Descriptive statistics

Descriptive statistic is a methodology used frequently by many researchers to collect and represent surveyed data for the purpose of explaining a certain phenomenon. Data usually collected through structured questionnaire survey presenting targeted population. The data are stored in tables form and presented by Bar graph or pie chart. The main idea of graph presentation for easy understanding and get overview of data distribution for different variables through basic statistics such as standard deviation and mean. It’s necessary to conduct descriptive analysis before proceeding with model development or any statistics test. In this stage, researcher try to spot pattern or explore connections so the worth full data can be formed as group where related data fall into same group. According to (Hand et al., 2001). Stated that most powerful methodologies applied is clustering analysis. Therefore, in this research a descriptive analysis developed in first part of questionnaire survey distributed among construction decision makers.

3.4 Prediction statistics:

The second part of discovery data mining focuses on data prediction using modeling and statistical tests to discover trends and data behavioral. The main aim is to make prediction and forecast future instances based on model built in using historical data. The prediction statistics is divided into two subgroup, classification and regression. Differences between two models can be summarized that classification model attribute target is categorical while regression model are quantitative or numerical (Hand et al., 2001). Data mining using various algorithms and statistical techniques such as, classification, fuzzy logic, genetic algorithms, neural networks used as applications for regression algorithms, decision algorithms. Following table showing pros and cons of some classification techniques :(David and Rubeaan, 2013; Rao, and Chandu, 2017; Sagar, 2015; Tomar, 2013).

Table 2. Pros And Cons Of Classification Techniques

	Pros	Cons
Decision Tree	• It can minimize the ambiguity of complicated decision. • Easy to be interpreted. • It is powerful and straight forward classification algorithms. • It can deal with high dimensional data.	• Over fitting. • Impacted via noise data. • It generates complex decision tree in case of numeric dataset used. • It generates categorical output.

	Pros	Cons
	• It is simple for understanding and efficient for practical problem. • It can handle models based on numerical and categorical data.	
Bayesian Network	• Powerful probabilistic representation tool. • Graphical model. • High accuracy and speed for huge dataset. • It handles computations process easier.	• Lack of probability data. • It depends on the assumption which, is made in class conditional. • It is required a very large of data records to obtain a good result. • Lack of result accuracy in case where their dependency between variables.
Support Vector Machine	• It is a robust and delivers a unique solution. • It can be designed for classification and regression problems. • High accuracy compared to another classifier. • It can handle over fitting problem. • It can handle nonlinear data points.	• High algorithmic complexity. • It requires extensive memory during programming in large-scale tasks. • Training process takes long time. • It's complicated to be used in problems rather than binary outcome. (Multi class)
K- Nearest Neighbor	• Training process is done fast. • It can be implemented easily. • It can perform well in several cases. • It can handle not linear separable.	• The result can be sensitive to the data noise when the k value is either too small or tool large. • It is slow in classifying test tuples. • Impacted when the nearest neighbors are very widely in their distance. • Large storage requirements. • Testing process is slow.
Artificial Neural Network Algorithm	• Easy to use and easy to implement. • Applicable to a wide range situation. • It can handle noisy dataset. • It can handle complex relationship between independent and dependent variables.	• High processing time is required if network is large. • Difficult to figure out how many layers and neurons are needed. • Difficult to understand the decision making process' black box". • Over fitting can be problem. • It's difficult to be interpreted if large neural network exists.

3.4.1 Classification

Classification is the most commonly technique used in data mining, which either uses decision trees or artificial neural networks (Magesh et al., 2013). In terms of definition, it can be defined as data analysis tool to develop prediction model that describes valued information. For example, before project execution and using classification process to distinguish whether the project is feasible or not. Obviously, classifier is required to predict risk levels of proposed project. In general, classification process is a two-step process: in the first step, Learning Step (Training Phase) where different algorithms are used to construct the classifier model through using of training data set gathered and their associated categories labels. The main purpose of this step to train the model the prediction of result accuracy. The second step is using the classifier for classification and estimate the accuracy of classification rules.

3.4.2 Decision Tree development

Quinlan (1986) asserts that the concept of machine learning has been under area of research since the recognition of artificial intelligence as a discipline during the 1950s. This is possible because of two reasons. Firstly, academics and researchers are interested in understanding intelligent behavior and intelligence in context of learning. Secondly, this learning has the potential to create and design artificial systems. As quoted by Quinlan (1986), early research on intelligent systems have shown that such learning can be incorporated in these systems to produce self-improving programs, solving problems and structuring knowledge. Such systems utilize knowledge that is explicitly represented or modeled rather than being embedded in algorithms. Based on this concept, decision trees have been developed by Quinlan (1986).

3.4.3 Decision Tree

Decision trees have been identified as the most influential and useful classification technique that is utilized in the field of data mining. A decision tree is considered to be an instrumental tool that supports decision making process as it translates the inputs into a tree-like model with their different outcomes that includes the “utility, costs of resources, and chance event outcomes” (Leka and Caushi, 2019). Decision trees are useful in managing two types of data sets: categorical data and numerical data (Rajalakshmi et.al., 2012). It’s considered as the easiest for the humans in terms of result interpretation capabilities provided compared to other techniques complexity.

According to Magesh et al. (2013), decision tree considered to be a model that is in the shape of tree, having different branch nodes. The tree starting with root node at the highest-level following branch node where the data is branched using some section measure. Each branch node is responsible for representing a choice between alternatives based on the number of substitutes available. The leaf node in the model is responsible for representing a categorical or numerical decision (Magesh et.al, 2013). Complexity of the tree can be measured by either counting the total number of leaves or nodes or based on tree depth used. Constructing of decision tree can be expressed as following, firstly attribute selection to place it in the root node and two or more branch for each option value. Then, splitting process to form subsets for every value of attribute and repeating this process till stopping where the node has same classification value. The researcher (Vandamme et al., 2007)., pointed that the main differences between the various decision-tree-building algorithms is identified by the attribute that produces the best split in the data. Each decision tree algorithm has its own measure to select the attributes at each step while growing the tree. According to Loh (2011), Following comparison of classification tree methods representing the splitting criteria and features of each algorithms:

Table 3. Comparison Of Classification Tree Methods

Feature	CART	QUEST	CRUISE	GUIDE
Unbiased Splits		√	√	√
Split Type	U,I	U,I	U,I	U,I
Branches/Split	2	2	2	2
Interaction Tests			√	√
Pruning	√	√	√	√
Variable Ranking	√			√
Missing Values	s	i	i,s	m

i, missing value imputation; l, linear splits; u, univariate splits; s, surrogate splits; m, missing value category

3.4.4 *Advantages and Disadvantages of Decision Trees*

Decision trees has both advantages and disadvantages. The benefits of decision trees are discussed as follows:

1. Decision trees are known to be flexible and adaptable as they can be compacted to become understandable. In simple terms, decision trees can be understood by non-professional users because the model is straightforward and easy to understand. Furthermore, they can be changed into set of rules, making them clearer and more coherent. Decision trees are useful in classifying knowledge into trees, and thus facilitates the decision-making process.
2. Categorical and numerical datasets can be handled by decision trees (Magesh et al., 2013).
3. Nominal and numerical input attributes can be managed by decision trees
4. Decision trees can handle and analyze datasets that may contain errors and mistakes.
5. Decision trees supports the representation of “discrete-value classifier”.
6. Datasets having missed values can also be managed by decision-trees.
7. Decision-trees are not dependent on parameters and therefore, it is non-parametric in nature. This indicates that assumptions and suppositions are not required for placing inputs, classification or distribution of space.

While literature suggests that decision trees have several benefits, it has some disadvantages. The disadvantages of decision trees are discussed as follows:

1. Much of the algorithms related to the decision trees such as ID3 and C4.5 mandate the requirement of discrete values for the targeted attributes.
2. Decision trees algorithms are based on classification and therefore, they use the “divide and conquer” approach. In presence of highly relevant attributes, they exhibit superior performance. In case of complex interactions, their performance is hindered. The reason is that a classifier described by other classifiers is a complex and challenging issue since its representation in decision trees is difficult.
3. Quinlan (1986) suggests that since decision trees have the property of being greedy, it can make the training set over-sensitive. It can also assign attributes that are not relevant and can increase noise because of its greedy attribute (Quinlan, 1986, Maimon & Rokach, 2005).
4. Magesh et al (2013) suggests that decision trees have the problem of overfitting, which can decrease the learning accuracy of decision trees by 10% to 25%.

3.5 Decision Tree Algorithms Models

Notably, numerous studies have used several prediction models in their research and found either its difficult or time-consuming or lack of accuracy in prediction performance. Several statistics evaluation for decision tree algorithms carried out in order to create accurate prediction model. According to Ali et al. (2015) research who aimed to compare predictive performances of several datamining algorithms to conclude that Exhaustive CHAID algorithm was found as a good and significant predictor. Moreover, Karadas et al. (2017) tested predictive capabilities of Exhaustive CHAID, CART, and MLP algorithms resulting that the significance order in the predictive accuracy as following: Exhaustive CHAID >ANN>GLM >CART.

Moreover, Lim et al. (2000) investigated 33 prediction decision tree algorithms and compared them in terms of classification accuracy, complexity and training time. This study concluded that most accurate decision tree algorithm is QUEST as it's considered to have faster process time and less prediction error. Also, Caushi (2019) in his published thesis, examine four prediction algorithms in terms of accuracy and precision and the result clear that Exhaustive CHAID and QUEST techniques proved to be more efficient and accurate than others prediction techniques.

Thus, this study applied the most appropriate combination of best two approaches Exhaustive CHAID and QUEST models according to previous literature to forecast the potential risk in proposed project in early stage and compared their prediction performance in terms of accuracy and efficiency.

3.5.1 Exhaustive CHAID

CHAID stands for Chi-squared Automatic Interaction Detector. Exhaustive CHAID algorithm is a modified version of CHAID decision tree algorithm, which was developed by Biggs and Suen (1991) to overcome some of the latter weakness. The main difference of Exhaustive CHAID that examine all possible splits on each node and it's not stopping splitting process even if optimal split is found. Its keep merging the categories of predictor variable till only two sub-categories are left. It has three core steps: merging, splitting, and stopping (Novita and Effendy, 2015). A decision tree is created through these steps repeated on each node, initiating from the root node.

3.5.2 QUEST

QUEST is decision tree algorithm that is responsible for classification of the data and was introduced by Loh and Shih in 1997 (Loh, 2014). It has a splitting rule, which assumes that the targeted variable is continuous or uniform. In terms of calculation speed, it is efficient and fast compared to other methods. It also can neglect bias that is prevalent in other decision tree algorithms. It is generally believed that this algorithm is more appropriate for multiple category variables. However, it able to process binary data only.

In QUEST, input attribute and target attribute association for each split is calculated using ANOVA F-test or Levene's test or Pearson's chi-square (Rokach and Maimon, 2005). The former is used for attributes that are continuous and ordinal, whereas the latter is used for attributes that are nominal. For multinomial targeted attribute, two super classes are established through use of two-way clustering. For splitting, the attribute that has the greatest connection with the target attribute is used. Quadratic discriminant analysis (QDA) is used for determination of the optimum splitting point for the attribute that has been inserted as the input (Rokach and Maimon, 2005). QUEST gives decision trees that are binary in nature. For tree pruning, ten-fold cross-validation is utilized (Rokach and Maimon, 2005).

Loh (2014) asserts that QUEST has two steps, which are based on the "significance tests to split each node". During the first test, the association of each X with Y is tested. The variable selection is based on level of significance. The highest significant variable is selected. If each of the X is independent of Y, then each X has the same selection chance. As a result, selection bias is not present in this approach. QUEST uses different tests based on the nature of the variables (Loh, 2014). For categorical variables, it utilizes chi-squared tests. For ordered variables, analysis of variance tests is utilized.

3.6 Research Methodology

Research methodology can be defined as the process of collecting relevant data from various sources to validate the research. As initial step to meet the research objective, an extensive literature review discussed in previous chapter to benchmark previous methods applied in research that dealt with decision making process and examine the most significant go/no go decision factors. Several researchers investigate decision making theories to find a proper methodology for developing decision model and decision variable relationship where based on that, this study came out with new proposed methodology. Following this part, was data collection from several public or private construction organization through questionnaire survey distributed among their senior decision makers. In this research, a quantitative approach selected and using questionnaire designed to address and rank the most significant go/no-go decision factors at early stage of proposed project and build the go/no-go decision model based on decision tree algorithms.

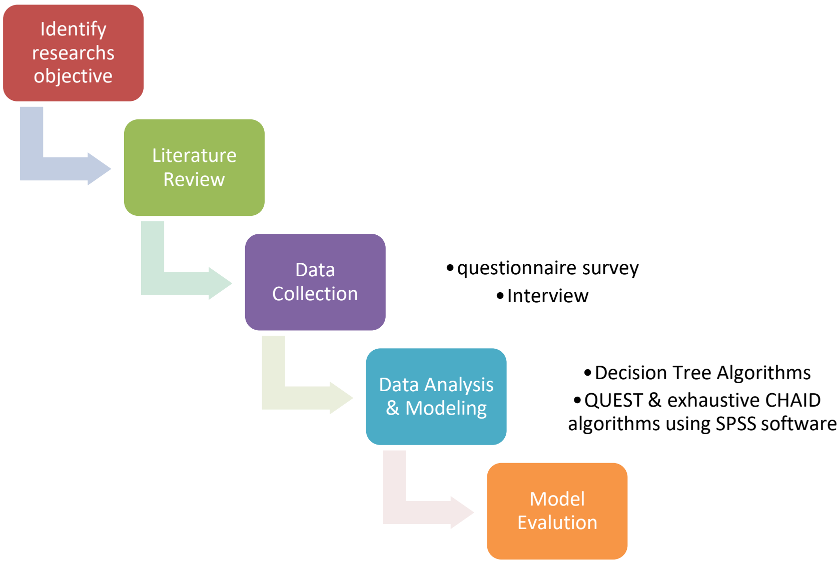

Figure 6. Research Methodology Steps

A statistical analysis program called "Statistical Package for the Social Sciences" (SPSS) is used in this paper to perform the data analysis part and to build the go/no-go decision model using the decision tree methods. The figure below shows the methodology steps used in this study.

3.7 Sampling Size Technique

Sampling technique is useful way to optimize the sample extraction criteria so same information can be obtained from entire population. In this study, Beta-probability distribution chosen to estimate sample size N of selected respondent (the participants' years of experience in the construction business). According to (Chisala, 2017; Roscoe, 1975; Wanous et al., 1998) following equation used to calculate sample size N:

$$N = \left[\frac{Z^2\sigma^2}{\varepsilon^2}\right] \text{ For } 30 \le N \le 500$$

Z is the z-value for 99% confidence interval $t_e \pm 2.0\ \sigma$ and ε is the margin of error.

- The standard deviation of normal distribution σ can be estimated as follow:

$$\sigma = \left(\frac{max.years - min.years}{6}\right)$$

- The mean number of years of normal distribution t_e can be determined as follow:

$$\text{te } = \left(\frac{max.years + 4M + min.years}{6}\right)$$

- The average number of contractor's experiences years M is can be estimated by using the following equation.

$$\text{M} = \left(\frac{max.years - min.years}{2}\right)$$

For this study, maximum years of experience is assumed to be 45 years, five year of experience as a minimum in the construction industry and the margin of error is assumed to be 2 years, σ = 6.66, Z = 2.58, ε = 2.0, hence N= 74. The response rate of 30% was expected to be filled and returned from the respondents. Thus, 200 questionnaires were distributed randomly among construction professionals. 95 out of 200 surveys were filled and returned by the respondents. The actual response rate was higher than expected (48%). The numbers of collected responses (95 participants) are more than the required sample size (74 participants). Therefore, the sample size of this study is valid.

3.8 Questionnaire Design

In order to observe the feedback of constriction profession, a questionnaire survey was structured in a form that necessary input data collected to build the decision tree model. A four pages questionnaire accompanied with a cover letter distributed for contractors and owner representatives (Client, construction management, owners and consultant). The cover letter indicated research objective and explained to the respondent that output result data would be used to study decision tree technique in project definition and planning stage of construction projects. Proposed model will improve the owners' ability to analyze and estimate the risk and strengthen his decision based on identified data.

The survey composed into three parts as following:

1. Basic personal and organization profile: (e.g., years of experiences, company size, work volume) to have different groups of the respondents for comparison and to develop go/no-go decision model.

Risk factors affecting go/ no go decision after project definition and planning stage of construction projects. The questionnaire structured in a way to examine the most significant risk factor based on practitioners' observation and to determine the relative significance of each risk group. Each participator requested to rank each risk factor on a scale from 1 to 5 by considering its importance. Rank 5 considered the highest risk level while 1 the lowest risk level contribution. A quantitatively weighting approach is adopted in this study to calculate the relative significance of project risks.

2. A scenario of go /no go decision: In this section, the respondents were requested to indicate how their company often takes go decisions in early stages after initial design completed for different scenarios of the four categories (Organizational, Project/Technical, Legal and Financial and Economic). 80 scenarios were developed and distributed to two forms (40 scenarios per questionnaire).

3.9 Statistical Tools

3.9.1 Exhaustive CHAID

Exhaustive CHAID, like CHAID, has three processes: merging, splitting, and stopping of the tree.

Process 1: Merging

The step involves in merging in exhaustive CHAID are discussed as follows:

1. The p-value will be 1 if predictor variable X has only 1 category.
2. The index will have zero value, the p-value will be calculated based on X's categories set in the given time. This p-value will be known as p (index)=p (0).
3. Else, determine the X categories in pair that are similar or least significantly different. This can be identified based on the pair that has the greatest p-value in terms of Y, which is the dependent variable. The method used to calculate the p value depends on the measurement level of Y. F-Test will be used if Y is continuous, two-way cross tabulation test if Y is nominal while likelihood-ratio test if Y is ordinal.
4. The pairs that have the greatest p-value will be combined to create the compound category.
5. This step optional. Binary split needs to be found if the compound category has three or greater than 3 original categories. The binary split that gives the lowest p-value needs to be identified. In case when the p-value is greater than the p-value of the compound category when combining in step 4, the binary split will be executed.

6. The index will be updated index=index+1. The p-value based on the X's categories will be determined. The p (index) will be represented as the p value.
7. The step 3 to 6 will be repeated till two categories are present. The set of categories having the smallest p (index) will be located.
8. If the category has less segment size as compared to user-identified least segment size requirement, it will be combined in the category that is similar to it using the greatest p-value.
9. Bonferroni adjustments will be used to determine the adjusted p-value.

Process 2: Splitting

For the identification of the best split for the predictor variable, it is identified during the merging step. This step identifies the best split for the given node. Selection of the best split is based on the p-value adjusted related to the predictor variable. The adjusted p-value is retrieved during the merging step. For splitting, the exhaustive CHAID uses the following steps:

1. Selection of the predictor that has the least p-value adjusted.
2. If this adjusted p-value is lower or equal to α split identified by the user, the node will be subjected to splitting with the given predictor. However, if this is not the case, it will become the terminal node.

Process 3: Stopping

The stopping process is dependent on four factors: split, depth of the decision tree, the least number of parent nodes available, and the least number of child nodes available (Novita and Effendy, 2015, Rischard, 2010).

Types of Predictor Variables in Exhaustive CHAID:

There are different types of predictor variables in Exhaustive CHAID as identified by Biggs, Ville and Suen (1991) and quoted by Novita, Sabariah and Effendy

(2015) in their research, are discussed as follows:

Monotonic: These types of predictor variables are the variables that are found in a sequence or ordinal scale. Each category has a value, which is different and cannot be same.

Free: These are types of predictor variables that don't follow a sequence and thus, are nominal. Each category is same.

Floating: These are the types of predictor variables in which one category placement in the ordinal scale is not known. The other categories are monotonic.

The p-value of chi-square is calculated in advance (IBM, 2019).

The p-value is determined after the chi-square value is retrieved (IBM, 2019).

3.9.2 QUEST

QUEST stands for quick, unbiased, efficient statistical tree, which is based on binary split decision tree algorithm. It is used for data classification and mining. It can be used in variety of combinations. These include linear or univariate combination splits. The unique aspect of QUEST that the bias in its attribute selection method is negligible. QUEST tree construction process comprises of split predictor selection, split point selection for the split predictor, and stopping.

Step 1: Selection of Split Predictor

The following steps are involved in split predictor selection:

1. X predictor that is continuous, for its ANOVA F test will be conducted to determine whether all of the categories of the dependent Y variable have common mean as that of X. The p-value is calculated. For categorical predictor, chi-square test for Y and X independence need to be calculated. Based on the chi-square test, the p value is determined.
2. The least p-value predictor is located and represented as * X.

3. For the least p-value that comes to be less than α / M, predictor * X will be chosen as the split predictor for the node. α is the significance level based on user specifications and M represents all the predictor variables identified. If least p-value is not less than α / M, then step 4 will be initiated.
4. When the least p-value exceed the value or is equal to the value of α / M, the following steps will be taken:
   - The Levene's F test needs to be determined for each of the X predictor, which is continuous. This is necessary to determine X's variances for different categories of Y have the same value. The p-value will be calculated.
   - Find the least p-value predictor variable and label it as **X
   - If this p-value is lesser than α / (M + M1), the split predictor will be **X. If this is not case, there will be no split predictor and the node will not be split. M1 is the number of continuous predictors.

Step 2: Split Point Selection

For the given node, when the X predictor variable has been subjected to splitting, the next step is to identify the split point. Using quadratic discriminant analysis (QDA) to find the best split point. QUEST is considered a binary tree, means the maximum splits are two from each node. However, if problem at hand with more than two classification, clustering two-means clustering method will be applied to group them into two superclasses by calculating the mean vector for all classification. The splitting will form group A where all classifications mean is identical while group B for the rest.

In case of X is a predictor variable is continuous, the split point identified directly using (QDA) While when the predictor variable nominal categorical, it will be transformed into continuous variables then (QDA) analysis to be applied.

The (QDA) estimates the distribution of the two formed groups (A, B) by calculating means and standard deviations from the samples and determine the split point as the point of intersection of the two Gaussian curves, being a root of the equation:

$$P(A|N)\frac{1}{\sqrt{2\pi}\,SA}\mathrm{e}^{-\frac{(x-XA)^2}{2SA}} = P(B|N)\frac{1}{\sqrt{2\pi}\,SB}\mathrm{e}^{-\frac{(x-XB)^2}{2SB}}$$

Where N is the node being split, XA, XB are the means and SA, SB are standard deviations of group (A, B). A quadratic equation then resulted from previous equation as following:

$$ax^2 + bx + c = 0$$

Where

$$a = {S_A}^2 - {S_B}^2$$

$$b = 2(\overline{X}_A {S_B}^2 - \overline{X}_B {S_A}^2)$$

$$c = (\overline{X}_B S_A)^2 - (\overline{X}_A S_B)^2 + 2S_A^2 S_B^2 \log\frac{n_A S_B}{n_B S_A}$$

Step 3: Stopping

The next step in the QUEST algorithm is stop, which determines if the tree growing needs to be stopped or continued. For QUEST, the following stopping rules have been identified:

1. For a node that is pure, the cases are grouped in the category of the same dependent variable within that node. In this case, node will not be subjected to splitting.
2. If the predictor values are identical in the node, it will not be subjected to splitting
3. The tree growing process will be halted as soon as the depth reaches the depth specified by the user.

4. Node will not be subjected to splitting if its size is less than the node size value identified and specified by the user.
5. The node will not be split if the child node of the split node is less than the value of user-defined child node size.

Missing Values

In QUEST, if the case of the dependent variable is missing, it will not be included in the analysis. For the given case if all the predictor values are not present, the case will not be included. Same is the case if the frequency weight is either negative or zero. To deal with the missing data for the predictor variables, a surrogate split method needs to be adopted. Surrogate splits definition and calculation in QUEST are similar to that of CART algorithm.

3.10 Model Validation

3.10.1 Relative Importance Index (RII)

In order to identify the importance of each risk factors that affecting owner decision whether to go or not with certain project, respondent was asked to assign numerical value from scale 1 to 5 for each factor that affection decision making. This scale later transformed to a Relative Importance Index (RII) for all factors. Relative Importance Index (RII) can be defined as method used to analyze the relative importance for each factor affecting certain phenomena through data collected from questionnaire survey. Each risk factor is calculated by multiplying its impact by its frequencies based on respondent view. Gunduz et al. (2013) used mathematical formula in his paper to calculate (RII) as following:

$$\boldsymbol{RII = \frac{\sum W}{AxN}}$$

Where:

W: the weight given to each factor by the respondents (ranges 1 to 5)

A: the highest ranking available which is 5.

N: the total number of respondents that have answered the questionnaire.

3.10.2 Spearman's Correlation

Spearman's Correlation can be defined as statistical measure of the strength of a relationship between paired data.

The value of the correlation coefficient r_s range constrained between $-1 < r_s < 1$. The closer value to -1 or +1 the stronger relation exist while zero indicates no relation between variables (Faridi and El-Sayegh, 2006).

A comparison between all Go/no-Go categories (Organizational related factors, project related factors, Legal factors, financial factors) and the total level of importance will be performed to determine the type of the relationship between two groups. According to Jarkas et al., (2014) the Spearman's Correlation $\boldsymbol{rs}$ is calculated by the following equation:

$$\boldsymbol{r_s = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)}}$$

Where:

d: the difference between ranks is assigned to variables for each factor

n: the number of rank pairs (which is equal to the number of Go/no-Go factors which is 23).

3.10.3 One-Way ANOVA Test

Analysis of variances (ANOVA) is identified a statistical method that focuses on the comparison of different samples' mean. The purpose of ANOVA is to find whether significant difference can be found between the class means through two or more independent groups (Ostertagová et al., 2014). It is primarily utilized to analyze variances when the data is subjected to division to form different groups or classes by a single factor (Ostertagová et al., 2014). (ANOVA) test considered an omnibus test statistic as it can't specify exactly which categorical group has significantly difference compared to other groups. However, prior of using this test there is a process to check whether the data need to be analyzed is suitable for this test and passes the six (ANVOVA) assumption. Failure to meet one of below assumption might lead to invalid result:

1. Interval or ratio level measurement should be used with the dependent variable.
2. Minimum of two categorical should be considered for the independent variable.
3. Observations in each group should be independent.
4. The data should be clear from significant outlier or unusual patterns.
5. Dependent variable should be normally distributed for each category of independent variable.
6. Homogeneity of variances is needed.

3.10.4 Tukey Method

Turkey test or also known as Turkey's range test is a statistical technique that is used to identify means that are different on basis of significance. It is responsible for comparing the means of pairs that are possible. Since this research uses ANOVA, the significance difference found between groups need to be compared to identify all possible pairs to identify the mean that is significantly different (Abdi and Williams, 2010). Turkey's method compares in pairs as this technique increases the efficiency of significant difference effectively in pairs.

CHAPTER 4: DATA ANALYSIS AND DISCUSSION

4.1 Introduction

The aim of this study is to propose simple decision model for owners (public or private) to aid them in go or no/go decision. This chapter shows all the data analysis and discussion of results. Firstly, the descriptive statistics of respondents (company size, Project size) will be presented. Consequently, the study will present the reliability test and Relative Importance Index (RII) to rank the factors affecting the go/ no go decision in early stage of project. Following that, a ranking comparison will be held amongst go/no-go categories factors using one- way ANOVA Test amongst respondents. Finally, the decision tree techniques will be applied to analyze project risk. A total 100 respondent from construction background were divided into training and testing groups in proportions of 80% and 20% respectively. Models were constructed using the two algorithms, namely Exhaustive CHAID, and QUEST. As stated in previous chapter, the algorithms were selected in this research based on their characteristics and prediction accuracy. Lastly, the models were validated using split-sample validation to determine its prediction performance.

4.2 Descriptive Statistics of the Respondents

4.2.1 Work Experience in Construction Projects

Figure 7. Work Experience Distribution

Importantly, the target of the respondent for this study was the professionals who have enough experiences in the construction industry. According to above figure that shows respondents with over than 5 years' experience in construction have the largest portion of the respondents with total 58%. Total 15% of the respondents have experiences in construction between 6-10 years. Also, same 15% percentage of the respondents have experiences in construction between 16-20 years and those who have experience over 21 years. Less than half of the respondents have experiences in the construction industry between 1-5 years and forming 42% of the total respondents.

4.2.2 Company Sector

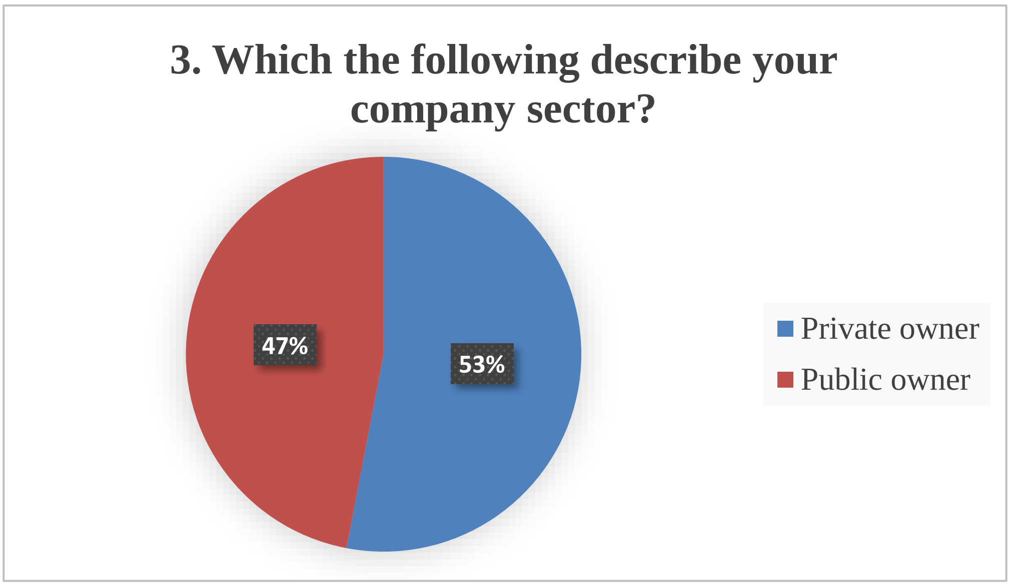

Figure 8. Company Sector Distribution

According to above chart, almost half of the respondents where private owner with total 53%. On the other hand, 47% of respondents where from different public sectors either governmental or consultant or construction management companies.

Taken to consideration that same number of questionnaires distributed among both private and public sector but feedback from public owner who completed the questionnaire and replied was less than expectation.

4.2.3 Company Size

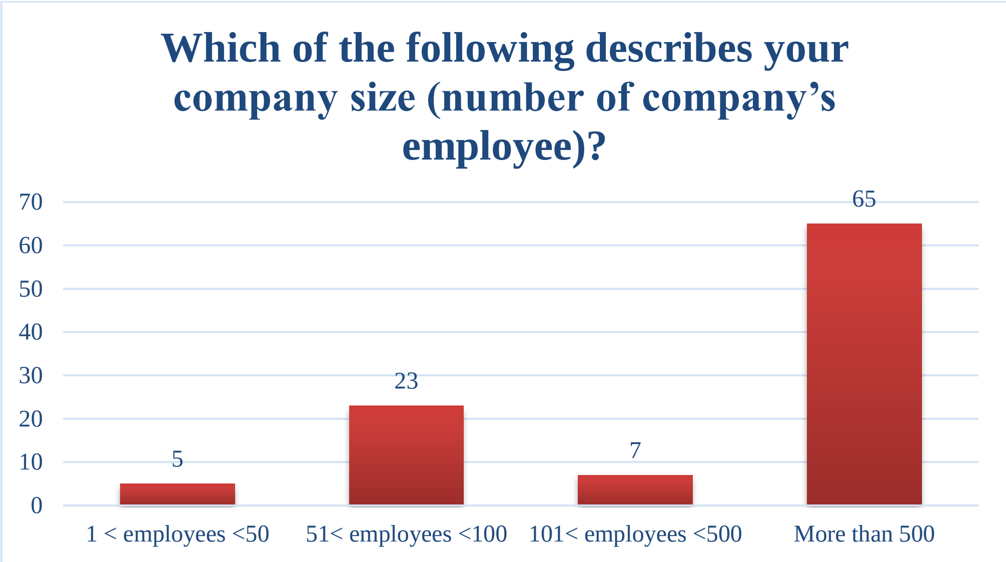

Figure 9. Company Size Distribution

According to above histogram, approximately two-thirds of the participants (65%) are working in project with number of stuffs more than 500 people. This indicate how scope of the work are complicated and large. Thirty per cent of those surveyed are working on company with number of employees range from 51 to 500 employees while just a small number of 5% respondents are working in small company which have range from 1 to maximum 50 employee. Thus, in this research we will consider only medium and large companies in our analysis since the feedback reported from small company is minor.

4.2.4 Project Size

As reported in previous question that most of respondent are working in medium to large company, thus result of this question expected to illustrate that work volume handled for these company over last five years is huge. The majority of respondent are working in projects worth between $101 and $500 million with more than half of the participations (57%). The number reduced extremely in project worth between $1 and $5 million with only 3 respondents.

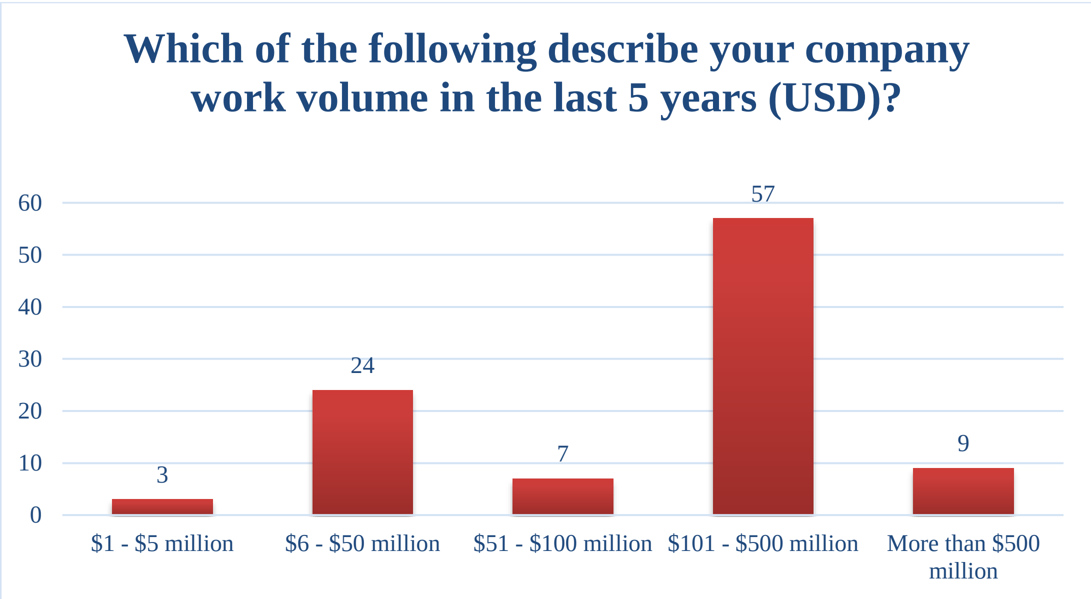

Figure 10. Project Size Distribution

4.2.5 Project stage that proposed model should be performed

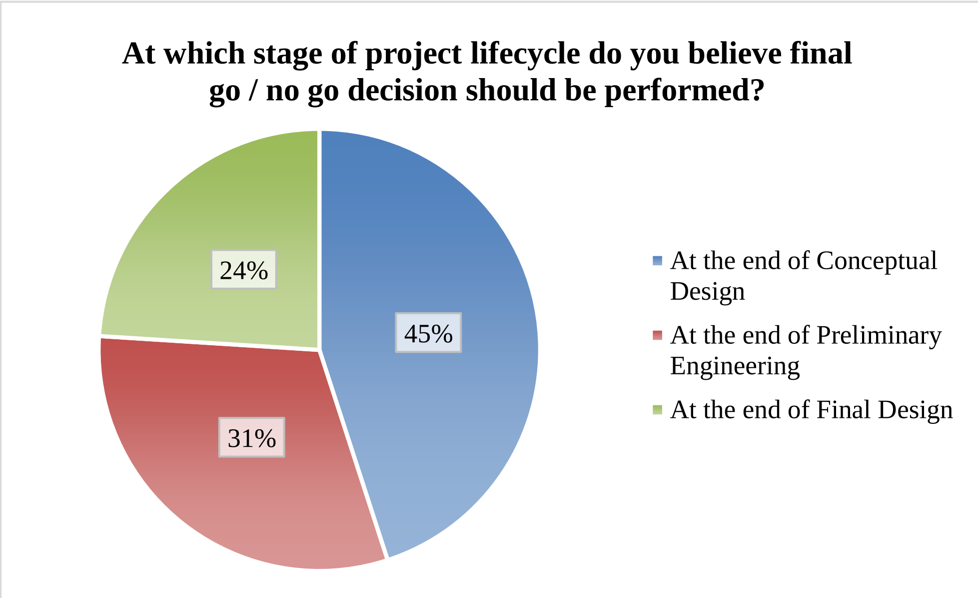

Figure 11. Percentages Of Project Stage To Perform Proposed Model

The question aimed to find the optimal stage that proposed decision model should be performed in early stage of the project. The discussion was about which of the following stages: at the end of conceptual design or at the end of preliminary engineering or at the end of final design. According to above par chart that indicates the feedback percentage obtained from respondent point of view, almost half of participation believe that go/no-go model should be performed at the end of conceptual design. The researcher agreed with this point of view as it will save unneeded cost in presence of project rejection where money wasted in resources charge and final design expenses. Just a small number of 24 respondents believe it should be conducted at the end of final design. Overall, this question conclude that proposed go/no-go model will be conducted after conceptual design stage by decision maker or owner.

4.3 Reliability Test

Table 4. indicates the reliability of respondents with Cronbach's Alpha with 0.877, which means the reliability of the received questionnaires is valid and acceptable.

Table 4. Reliability Test

Cronbach's Alpha	N of Items
0.877	23

4.4 Ranks of the Factors Affecting the Go/ No Go Decision in Early Stage of project

Table below indicates the Relative Importance Index (RII) values and ranking of key go/no-go factors; the RII was calculated each factor based on importance scale values by respondents from all the participants in this study. The respondents were requested to rate the level of importance of the 23 factors that influence the go/ no go decision in the early stage project. Likert scale 1, 2, 3, 4 and 5 were defined as follow 1 = very low importance, 2 = low importance, 3= medium importance, 4= high importance and 5= very high importance.

Table 5. Factors Influencing Go/No Go Decisions Of Owner In Early Stage Of Project

Code	Factors	1	2	3	4	5	W	RII	Factor Group Rank	Overall Rank	Group Rank
	Organizational Risk Factors							**0.756**			**1**
OF1	Financial stability of Owner	2	0	13	29	56	437	0.874	1	1	
OF2	Consultant, Suppliers reliability and experience in construction	1	3	35	40	21	377	0.754	2	5	
OF3	Design Errors and Omissions (Rush design)	2	7	34	29	28	374	0.748	4	9	
OF4	Qualification of Designers & planner	2	8	28	36	26	376	0.752	**3**	7	
OF5	Availability of skilled and unskilled workers / labors	5	10	37	36	12	340	0.68	6	21	
OF6	Availability of reliable and experience contractors	2	7	28	50	13	365	0.73	5	11	
	Project/Technical Risk Factors							**0.71**			**3**
PF7	Availability (materials & equipment)	1	4	30	44	21	380	0.76	1	4	
PF8	Erroneous geological condition study	3	14	34	30	19	348	0.696	5	17	
PF9	Availability of construction technologies / and skills	1	10	42	41	6	341	0.682	6	20	
PF10	Size and location of project	7	14	32	28	19	338	0.676	7	22	
PF11	Safety level required	6	16	15	32	31	366	0.732	3	10	
PF12	Clarity or Complexity of the design and scope	3	11	27	40	19	361	0.722	4	12	
PF13	Site space constraints	4	19	33	30	14	331	0.662	8	23	
PF14	Tight schedule	3	10	23	38	26	374	0.748	2	8	
	Legal Risk Factors							**0.705**			**4**
LF15	Excessive approval procedures in administrative government departments	2	12	36	26	24	358	0.716	1	13	
LF16	Country specifications and standards level in regulations and permits	3	10	34	35	18	355	0.71	2	16	
LF17	Lack of legality and standard dispute settlement procedure	2	13	40	29	16	344	0.688	3	19	
	Financial and Economic Risk Factors							**0.747**			**2**
EF18	Underestimated budgeting	0	5	19	32	44	415	0.83	1	2	
EF19	Inflation and deflation	2	14	34	35	15	347	0.694	6	18	
EF20	Price escalation of raw materials	2	11	31	39	17	358	0.716	5	15	
EF21	Expected return level/Project profitability	2	8	25	41	24	377	0.754	3	6	
EF22	High overhead cost.	0	6	27	42	25	386	0.772	2	3	
EF23	Forecast about market demand / Potential level of competition	1	10	32	44	13	358	0.716	4	14	

The above table revealing the relative importance of each factor affecting owners' go/no-go decision in early stage of the construction project. Obviously, the top three ranked factors found in Organizational category are: 1) Financial stability of Owner, 2) Consultant, Suppliers reliability and experience in construction, 3) Qualification of Designers and planner, and the 3 top ranked factors in project /technical category are: 1) Availability of materials and equipment, 2) Tight schedule, 3) Safety level required, and the top ranked factor in Legal category is the Excessive approval procedures in administrative government departments. Last category was Financial and Economic and the 3 top ranked factors in this category as following: 1) Underestimated budgeting, 2) High overhead cost, 3) Expected return level/Project profitability. The second part of the analysis was calculating the average RII value per category. Generally, result of RII values was quite close to each other but significantly, Organizational category has the highest importance value equal to 0.756 with unremarkable difference equal to 0.009 with the second ranked Financial and Economic category. Project /technical category is ranked as the third since it's RII value was slightly less than the latter's. Consequently, Legal category marked as the fourth one as it has the lowest RII value equal to 0.705.

Following table gives the rank of go/no-go factors among all the categories based on RII values. The table indicates that "Financial stability of Owner" is considered as the most important factor that inhibits the owners' decision with RII of 0.87. This was followed by "Underestimated budgeting" with an RII of 0.83. The other factors making up the leading top ten factors in order of the ranking are: 3) High overhead cost; 4) Availability (materials & equipment); 5) Consultant, Suppliers reliability and experience in construction; 6) Expected return level/Project profitability;

7) Qualification of Designers & planner; 8) Tight schedule; 9) Design Errors and Omissions (Rush design); 10) Safety level required. The Factor that was ranked lowest is Site space constraints with RII value equal to 0.662.

Table 6. Ranks Of Factors Influencing Go/No-Go Decisions From The Highest To The Lowest

Code	Factors	1	2	3	4	5	W	RII	Overall Rank
OF1	Financial stability of Owner	2	0	13	29	56	437	0.874	1
EF18	Underestimated budgeting	0	5	19	32	44	415	0.83	2
EF22	High overhead cost.	0	6	27	42	25	386	0.772	3
PF7	Availability (materials & equipment)	1	4	30	44	21	380	0.76	4
OF2	Consultant, Suppliers reliability and experience in construction	1	3	35	40	21	377	0.754	5
EF21	Expected return level/Project profitability	2	8	25	41	24	377	0.754	6
OF4	Qualification of Designers & planner	2	8	28	36	26	376	0.752	7
PF14	Tight schedule	3	10	23	38	26	374	0.748	8
OF3	Design Errors and Omissions (Rush design)	2	7	34	29	28	374	0.748	9
PF11	Safety level required	6	16	15	32	31	366	0.732	10
OF6	Availability of reliable and experience contractors	2	7	28	50	13	365	0.73	11
PF12	Clarity or Complexity of the design and scope	3	11	27	40	19	361	0.722	12
LF15	Excessive approval procedures in administrative government departments	2	12	36	26	24	358	0.716	13
EF23	Forecast about market demand / Potential level of competition	1	10	32	44	13	358	0.716	14
EF20	Price escalation of raw materials	2	11	31	39	17	358	0.716	15
LF16	Country specifications and standards level in regulations and permits	3	10	34	35	18	355	0.71	16
PF8	Erroneous geological condition study	3	14	34	30	19	348	0.696	17
EF19	Inflation and deflation	2	14	34	35	15	347	0.694	18
LF17	Lack of legality and standard dispute settlement procedure	2	13	40	29	16	344	0.688	19

Code	Factors	1	2	3	4	5	W	RII	Overall Rank
PF9	Availability of construction technologies / and skills	1	10	42	41	6	341	0.682	20
OF5	Availability of skilled and unskilled workers / labors	5	10	37	36	12	340	0.68	21
PF10	Size and location of project	7	14	32	28	19	338	0.676	22
PF13	Site space constraints	4	19	33	30	14	331	0.662	23

4.5 Ranking Comparison amongst Go/No-Go Categories Factors

To statistically ascertain this observation, an inferential statistical test was conducted between all go/no-go categories (Organizational related Factors, Project/Technical related Factors, Legal related Factors, Financial and Economic related Factors) and the total level of importance. The analysis used the spearman rank correlation coefficient to test the strength of the relationships between each category with others, then to find out which category has the strongest correction to the total level of importance on the early stage.

As stated in previous chapter, the Spearman's rank correlation coefficient range is between +1 and -1, where +1 indicate perfect positive correlation and -1 shows a perfect negative correlation. The null hypothesis is rejected when P-value is less than Alpha α (level of significance) Alpha equal to 0.01. Otherwise, fail to reject the null hypothesis.

The result of this test is revealed in table 7, a strong positive correlation between project factors and legal factors with coefficient equal to 0.696 indicating a strong relationship. Overall, the Spearman's correlation coefficient is higher than 0 and positive for all comparison, and the p-value is less than 0.01 for all comparisons, thus means a positive relationship is exist between every two categories. The correlation between financial and economic category and organizational category noteworthy relationship since the coefficient founded to have the smallest value equal to 0.268.

Table 7. Ranking Comparison Amongst Go/No-Go Categories Factors

		Project/Technical Risk	Legal Risk	Financial and Economic Risk	Total Risk
Organizational Risk	Correlation Coefficient	.572	.368	.278	.749
	P-Value	<0.01	<0.01	<0.01	<0.01
Project/Technical Risk	Correlation Coefficient		.696	.317	.886
	P-Value		<0.01	<0.01	<0.01
Legal Risk	Correlation Coefficient			.284	.727
	P-Value			<0.01	<0.01
Financial and Economic Risk	Correlation Coefficient				.585
	P-Value				<0.01

The table also shows that there is a strong and positive relationship (r=0.886, value < 0.01) between Project/Technical factors and the total level of importance which, is the strongest relationship among all the comparison, there is also strong and positive correlation (r=0.749, P-value < 0.01) between organizational factors and total level of importance.

4.6 One- Way ANOVA Test amongst Respondents

4.6.1 ANOVA- Company sector & company size

The primary target of applying statistical One-way ANOVA technique is to examine the potential of differences and degree of disagreement among the respondents:

Company sector:

One-way ANOVA analysis test also applied on company sector to discover if there is association with categories go/no-go factors that might be affected by respondent organization sector. Obviously, almost all P-values are close to 0.5 which is higher than 0.05 according to below table:

Table 8. ANOVA Comparison Amongst Respondents – Company Sector

ANOVA		
Category go/no-go Factors	Company Type	P-Value
Organizational Risk	Between Groups	0.475
Project/Technical Risk	Between Groups	0.240
Legal Risk	Between Groups	0.462
Financial and Economic Risk	Between Groups	0.388
Total Risk	Between Groups	0.329

Table 8. show the result of all P-values between groups are higher than threshold value 0.05. This conclusion lead that there are no significant differences between the opinions of company sector respondents on the importance level of the go/no-go factors categories.

Company Size:

Also, ANOVA comparison test applied on company size and below result found using SPSS software:

Table 9. ANOVA Comparison Amongst Respondents – Company Size

ANOVA		
Category go/no-go Factors	Company Size	P-Value
Organizational Risk	Between Groups	0.294
Project/Technical Risk	Between Groups	0.234
Legal Risk	Between Groups	0.130
Financial and Economic Risk	Between Groups	0.505
Total Risk	Between Groups	0.295

As can been see from table 9, all P-values are higher than the threshold. The same conclusion obtained in previous two dependent variables showed in this result that no significant differences between the opinions of company size respondents on the importance level of the go/no-go factors categories. To conclude, Job rule, company sector neither company size respondent has influence on go/no-go categories factors.

4.6.2 ANOVA for Project Size and Years of Experience

Table 10. ANOVA Comparison Amongst Respondents – Project Size

ANOVA		
Category go/no-go Factors	Project size	P-Value
Organizational Risk	Between Groups	0.093
Project/Technical Risk	Between Groups	0.188
Legal Risk	Between Groups	0.014
Financial and Economic Risk	Between Groups	0.734
Total Risk	Between Groups	0.098

From the above table, based on project size of the respondents, that P-values between groups is higher than 0.05 for Organizational related factors (P-value= 0.093), Project/Technical factors (P-value= 0.188), Financial and Economic factors (P-value=

0.734). However, there are one statistically significant difference on go/no-go groups, legal factors (P-value=0.014 less than 0.05).

The analysis result shows that size of the project lead to differences between the opinions of respondents on the importance level of the legal related go/no-go factors on early stage decision. Multiple comparisons using Tukey for legal factors and the respondents based on the project size are used to determine which size of project leads to the disagreement and which element.

Table 11. Multiple Comparison Using Tukey For Project's Factors Based On Project Size

Dependent Variable			Mean Difference	P-Value
Legal Risk	$1-$5 Million	$6-$50 Million	-1.5714	0.030
		$51-$100 Million	-1.3333	0.076
		$101-$500 Million	-1.6111	0.008
		More than $500 Million	-1.5906	0.006
	$6-$50 Million	$1-$5 Million	1.5714	0.030
		$51-$100 Million	0.23809	0.972
		$101-$500 Million	-0.0396	1.000
		More than $500 Million	-0.0192	1.000
	$51-$100 Million	$1-$5 Million	1.3333	0.076
		$6-$50 Million	-0.2380	0.972
		$101-$500 Million	-0.2777	0.885
		More than $500 Million	-0.2573	0.882
	$101-$500 Million	$1-$5 Million	1.6111	0.008
		$6-$50 Million	0.0396	1.000
		$51-$100 Million	0.2777	0.885
		More than $500 Million	0.0204	1.000
	More than $500 Million	$1-$5 Million	1.5906	0.006
		$6-$50 Million	0.0192	1.000
		$51-$100 Million	0.2573	0.882
		$101-$500 Million	-0.0204	1.000

First a translation of the numerical expression of project size to short word description as following classification: Small project ($1-$5 Million), Medium project ($6-$50 Million), large project ($51-$100 Million), very large project ($101-$500 Million), mega project ($101-$500 Million).

According to Table 12, following outcomes can be briefly discussed:

The respondents who are working in small and medium project have a significant difference between their opinions regarding the level of importance of some Legal' go/no-go related factors (at least one factor or more) since p-value equal to 0.03 less than threshold. Also, the mean difference between respondents who are working in small and very large project extremely high compared to other groups, this indicates that level importance of the legal related factors (at least one factor or more) in the early stage process is significantly differ from project size to another. Lastly, another difference found between respondents who are working in small and mega project on their opinions on level of importance of the legal go/no-go related factors (at least one factor or more), the table below is summary result of Multiple Comparisons for each go/no-go factors with each project size:

Table 12. Post Hoc Tests - Multiple Comparisons Using Tukey For Project Size

Code	Attribute – Project Size	P-value
	Small Project vs Mega Project	
LF17	Lack of legality and standard dispute settlement procedure	0.009
	Small Project vs Very large Project	
LF17	Lack of legality and standard dispute settlement procedure	0.007

It’s obvious that Lack of legality and standard dispute settlement procedure factor is the main reason behind the difference in opinion between people who are working in mega project and small project overall the legal category. This result can be translated that small project rarely exposed to legal disputes because of their simplicity nature. On other hand, it’s logical that mega project is more exposed to legal disputes between parties involved. Also, the standards and codes followed in mega project are extensively complicated compared to simple project. Thus, a difference in respondent opinion is expected.

Years of Experience:

Final step of using one-way ANOVA test is to examine how years of experience of respondent are importance to the other groups. Following table 13. showing analysis result conducted for last group in this research:

Table 13. ANOVA Comparison Amongst Respondents – Years Of Experience

	ANOVA	
Category go/no-go Factors	Years of experience	P-Value
Organizational Risk	Between Groups	0.494
Project/Technical Risk	Between Groups	0.811
Legal Risk	Between Groups	0.842
Financial and Economic Risk	Between Groups	0.012
Total Risk	Between Groups	0.624

The conclusion of above table can be summarized that most of P-values between groups are higher than the threshold 0.05. It was found that P-values for the independent categories as following: Organizational related factors (P-value= 0.494), Project/Technical factors (P-value= 0.811), Legal factors (P-value= 0.842). However, the P-value of Financial and Economic factors (P-value= 0.012 less than 0.05), this lead there are differences between the opinions of experienced respondents on the importance level of the go/no-go factors for the latter category. Multiple comparisons using Tukey for Financial and Economic factors and the respondents based on year of experience are used to determine which range of years' experience leads to the disagreement and which factor.

Table 14. Multiple Comparison Using Tukey For Project's Factors Based On Years Of Experience

Dependent Variable			Mean Difference	P-Value
Financial and Economic Risk	1-5 years	6-10 years	-0.3076	0.459
		11-15 years	0.1666	0.875
		16-20 years	-0.4666	0.066
		More than 20	0.1111	0.969
	6-10 years	1-5 years	0.3076	0.459
		11-15 years	0.4743	0.207
		16-20 years	-0.1589	0.951
		More than 20	0.4188	0.324
	11-15 years	1-5 years	-0.1666	0.875
		6-10 years	-0.4743	0.207
		16-20 years	-.6333	<u>0.029</u>
		More than 20	-0.0555	0.999
	16-20 years	1-5 years	0.4666	0.066
		6-10 years	0.1589	0.951
		11-15 years	.6333	<u>0.029</u>
		More than 20	0.5777	0.058
	More than 20	1-5 years	-0.1111	0.969
		6-10 years	-0.4188	0.324
		11-15 years	0.0555	0.999
		16-20 years	-0.5777	0.058

First a translation of the numerical expression of years of experience to short word description as following classification: Beginner (1-5 Years), Junior (6-10 Years), Senior (11-15 Years), Manager (16 -20 Years), Director (More than 20 years).

According to Table 14, following result can be briefly discussed:

The respondents who are senior and managerial level have slightly significant difference between their opinions regarding the level of importance of some Financial and Economic go/no-go related factors (at least one factor or more) since p-value equal to 0.029 less than threshold. In order to identify exactly the factor that affect level of importance of decision, multiple comparisons for each go/no-go factor with each level of experience using Tukey method used and result are summarized in the table below:

Table 15. Post Hoc Tests - Multiple Comparisons Using Tukey For Years Of Experience

Code	Attribute – Years of Experience	P-value
	Senior Level vs Managerial Level	
EF18	Underestimated budgeting	0.017
	Beginner Level vs Managerial Level	
EF19	Inflation and deflation	0.025
	Director Level vs Managerial Level	
EF19	Inflation and deflation	0.018

Table 15. indicated that Underestimated budgeting founded is the main difference in opinion between senior and managerial employee level overall the Financial and Economic category. In addition to that, Inflation and deflation factor have different opinion between beginner employee and managerial level. The reason behind

this difference point out the awareness of inflation and deflation risk on decision making with managerial position are much understandable since they are experiencing closely and up to date with its impact on their running project while the beginner are rarely knowledgeable about inflation effect of decisions making. Unexpectedly, a difference in opinion founded between director and managerial level with P-value of 0.018 less than threshold value 0.05. As both levels are classified as decision maker level but still, they have different view regarding inflation and deflation factor overall the Financial and Economic category.

Multiple comparisons using Tukey for project size and number of years' experience are attached in appendix B.

4.7 Decision Tree Model for Owner

4.7.1 Using Exhaustive CHAID Method for Owner

Starting with analysis of using Exhaustive Chi-squared Automatic Interaction Detection algorithm. The table below presents the model summary:

Table 16. Exhaustive CHAID Model Specification

Model Summary		
Specifications	Growing Method	EXHAUSTIVE CHAID
	Dependent Variable	Go Decision
	Independent Variables	Organizational Risk, Project/Technical Risk, Legal Risk, Financial / Economic Risk
	Validation	Split Sample
	Maximum Tree Depth	3
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50

Model Summary		
Results	Independent Variables Included	Financial / Economic Risk, Legal Risk, Project/Technical Risk, Organizational Risk
	Number of Nodes	28
	Number of Terminal Nodes	17
	Depth	3

The summary table states the condition used in the calculation of EXHAUSTIVE CHAID algorithm. It's divided into two sections, namely, specification and results. Specification part gives insight about the details used to build this model. Also, the dependent and independent variables. The model predicts maximum tree depth equal to three with minimum cases in parent node equal to 100 and 50 in child node. Result part shows that total of 17 terminal nodes and total 28 nodes are presented in the model.

The visual structured model of EXHAUSTIVE CHAID tree-based algorithm used for the prediction of go/no go decision presented in figure 12. shows the following outcome:

- Financial / Economic Risk, Legal Risk, Project/Technical Risk, Organizational Risk are only the independent variables included.
- The modality with the highest value is the one that is highlighted with grey inside the node.
- Maximum tree depth is three which contain the most significant predictors of go/no-go decision.
- The best predictor of go/no-go decision for owner is Financial and Economic risk.
- As a response variable is depicted in Figure 12, it shows node zero at the top of the

constructed tree gave more than half of the prediction (55%) to not go with the project which it's financial and economic risk is high.

- In the first depth of the tree, root node was divided into the node 1, node 2 and node 3, low, medium and high categories.
- The next best predictor is legal risk level.
- If the financial and economic risk and risk level are high, the model shows 82% for no-go decision.

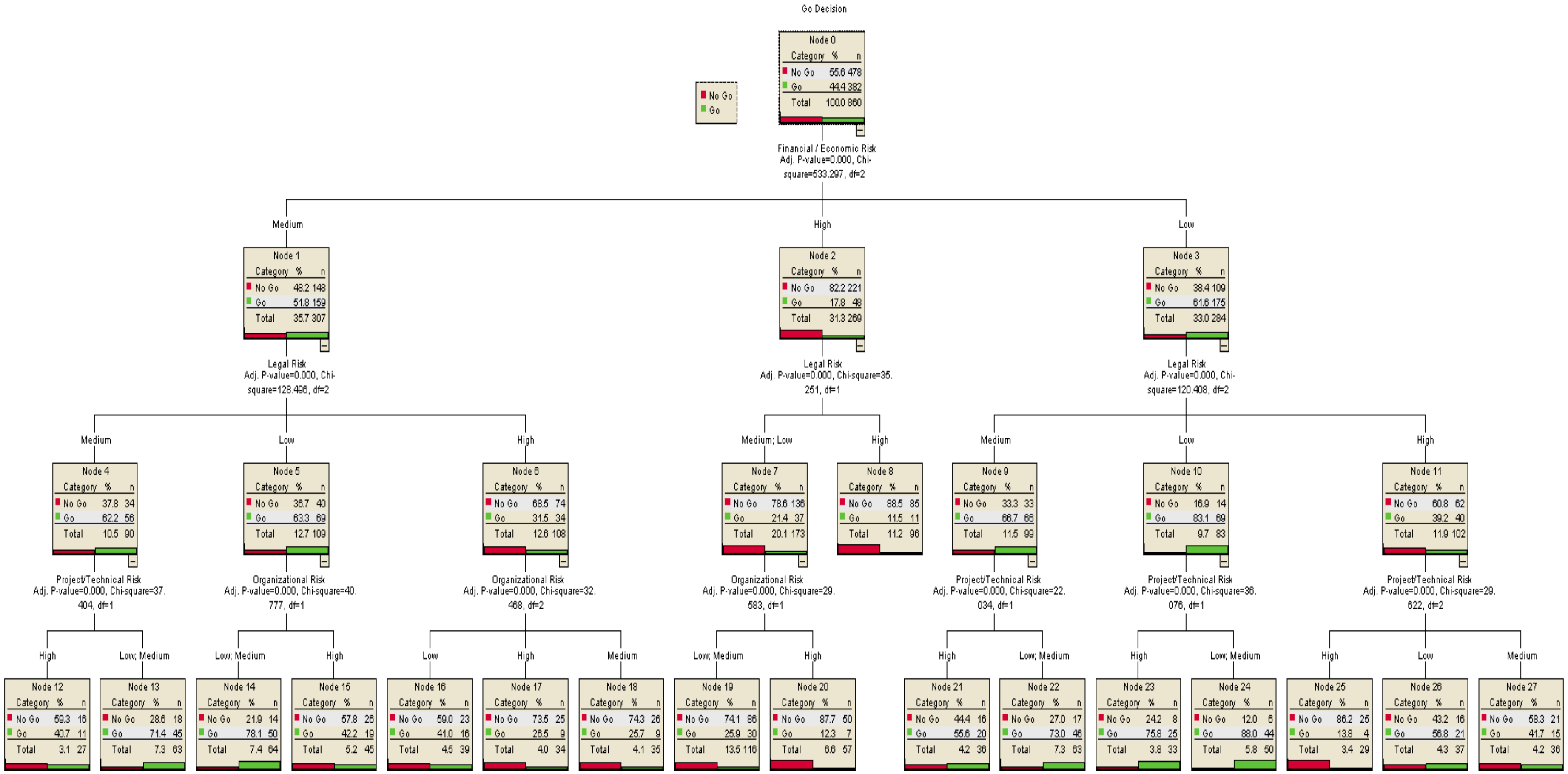

Figure 12. Decision Tree Go/No-Go Model For Owner Exhaustive CHAID Method

Table 17. presents the tree table for the go/no-go decision model for owner. The table tree demonstrates the structure steps of the tree diagram. It provides majority of the significant tree diagram information in a table format. For each node in the decision tree diagram, the table displays:

- The number and percentage of the go and no-go for each category.
- The parent node specified for each child node.
- The predicated category for the Go decision and the independent variables (Financial / Economic Risk, Legal Risk, Project/Technical Risk, Organizational Risk) used to divide nodes. Instance, for parent node 0, the Financial / Economic Risk has the highest Chi-square - level on the importance to the model among other categories, with three split values high, low and medium. For high split value, the predicated decision is no-go with 82%, and almost 18% is recommended to go for the project. By contrast, for low and medium Financial / Economic Risk level the predicted value is to go.
- The chi-square value, significance level (Sig) with Bonferroni adjusted and degrees of freedom (df) for each split value.
- The depth of the decision tree is three levels because the stopping criteria of exhaustive CHAID method do not find significant effects of others independent variables.

Generally, the owner or client should evaluate the 23 go/no go factors and calculated the average risk of each group. The model should be tracked from top "root node" to bottom "Child node" by decision maker. For example, it the average risk of financial and economical go/no-go factors is high and the legal risk also high, then no go decision should be considered for this project. Analysis of previous scenario as following, financial and economic risk is high (82.2% for no go) and legal risk is high too (68.5% for no-go), therefore, the predictive model recommend the owner to no go with the project as probability of failure is high. Point out that owner could stop at this node as other risks nodes are negligible because in this case, they do not have a significant influence on go/no-go decision.

However, the owner could a set risk management plan to reduce either the financial risk or legal risk to reevaluate the decision. Sometimes risk out of owner control as its governmental procedure where in this case owner is advised to not go.

Another example, assuming the case where the financial and economic risk is low (61.6% for go) and Legal Risk is low or medium (63%, for go) and Project/Technical Risk is low or medium (71.4% for go) and Organizational Risk is low or medium (78.1% for go), thus the model recommending to go with this project as the overall risk level exposed to this project are acceptable.

The variable with a high value of Chi-square indicates the level of importance of variable to the model; df is indicated the degree of freedom (the acceptable margin of error) for each split value. For instance, in table 17. the Financial / Economic risk group has the highest value of the Chi- Square. Therefore, it is selected as a root node of the decision tree.

Table 17. Decision Tree Table- Using Exhaustive Chaid

Sample	No Go		Go		Total		Predicted Category	Parent Node	Primary Independent Variable				
	N	Percent	N	Percent	N	Percent			Variable	Sig.[a]	Chi-Square	df	Split Values
0	478	55.6%	382	44.4%	860	100.0%	No Go						
1	148	48.2%	159	51.8%	307	35.7%	Go	0	Financial / Economic Risk	0.000	533.297	2	Medium
2	221	82.2%	48	17.8%	269	31.3%	No Go	0	Financial / Economic Risk	0.000	533.297	2	High
3	109	38.4%	175	61.6%	284	33.0%	Go	0	Financial / Economic Risk	0.000	533.297	2	Low
4	34	37.8%	56	62.2%	90	10.5%	Go	1	Legal Risk	0.000	128.496	2	Medium
5	40	36.7%	69	63.3%	109	12.7%	Go	1	Legal Risk	0.000	128.496	2	Low
6	74	68.5%	34	31.5%	108	12.6%	No Go	1	Legal Risk	0.000	128.496	2	High
7	136	78.6%	37	21.4%	173	20.1%	No Go	2	Legal Risk	0.000	35.251	1	Medium; Low
8	85	88.5%	11	11.5%	96	11.2%	No Go	2	Legal Risk	0.000	35.251	1	High
9	33	33.3%	66	66.7%	99	11.5%	Go	3	Legal Risk	0.000	120.408	2	Medium
10	14	16.9%	69	83.1%	83	9.7%	Go	3	Legal Risk	0.000	120.408	2	Low
11	62	60.8%	40	39.2%	102	11.9%	No Go	3	Legal Risk	0.000	120.408	2	High
12	16	59.3%	11	40.7%	27	3.1%	No Go	4	Project/Technical Risk	0.000	37.404	1	High
13	18	28.6%	45	71.4%	63	7.3%	Go	4	Project/Technical Risk	0.000	37.404	1	Low; Medium
14	14	21.9%	50	78.1%	64	7.4%	Go	5	Organizational Risk	0.000	40.777	1	Low; Medium
15	26	57.8%	19	42.2%	45	5.2%	No Go	5	Organizational Risk	0.000	40.777	1	High
16	23	59.0%	16	41.0%	39	4.5%	No Go	6	Organizational Risk	0.000	32.468	2	Low
17	25	73.5%	9	26.5%	34	4.0%	No Go	6	Organizational Risk	0.000	32.468	2	High
18	26	74.3%	9	25.7%	35	4.1%	No Go	6	Organizational Risk	0.000	32.468	2	Medium
19	86	74.1%	30	25.9%	116	13.5%	No Go	7	Organizational Risk	0.000	29.583	1	Low; Medium
20	50	87.7%	7	12.3%	57	6.6%	No Go	7	Organizational Risk	0.000	29.583	1	High

Sample	No Go		Go		Total		Predicted Category	Parent Node	Primary Independent Variable				
	N	Percent	N	Percent	N	Percent			Variable	Sig.[a]	Chi-Square	df	Split Values
21	16	44.4%	20	55.6%	36	4.2%	Go	9	Project/Technical Risk	0.000	22.034	1	High
22	17	27.0%	46	73.0%	63	7.3%	Go	9	Project/Technical Risk	0.000	22.034	1	Low; Medium
23	8	24.2%	25	75.8%	33	3.8%	Go	10	Project/Technical Risk	0.000	36.076	1	High
24	6	12.0%	44	88.0%	50	5.8%	Go	10	Project/Technical Risk	0.000	36.076	1	Low; Medium
25	25	86.2%	4	13.8%	29	3.4%	No Go	11	Project/Technical Risk	0.000	29.622	2	High
26	16	43.2%	21	56.8%	37	4.3%	Go	11	Project/Technical Risk	0.000	29.622	2	Low
27	21	58.3%	15	41.7%	36	4.2%	No Go	11	Project/Technical Risk	0.000	29.622	2	Medium

Growing Method: EXHAUSTIVE CHAID

Dependent Variable: Go Decision

a. Bonferroni adjusted

4.7.1.1 Model validation – Exhaustive CHAID Method for Owner

Split-sample is an evaluation technique used in predictive decision tree models by dividing the original sample into a training set to train the model, and a test set to evaluate it. In this model, 20% of the sample size is used to measure the accuracy of the model for future cases. Also, the decision model accuracy illustrated through Gain, response and index plots as validation graphical tools.

Table 18. Risk Table - Exhaustive CHAID Method for Owner

	Risk	
Sample	Estimate	Std. Error
Training	0.247	0.008
Test	0.263	0.015

According to above table, the risk estimate for the training sample is 0.247 indicates that the predicted value by the model (Go or No-Go) is wrong for 24% of the cases. In other words, the risk of misclassifying a go decision is approximately 24%. The estimated risk of the sample test is higher (26.3% of the all sample size) with a standard error of 0.015. That means the model classifying is incorrectly of approximately 26%. The Risk table 18, gives the right insights about the result of classification risk estimation of model accuracy:

Table 19. Classification Table - Exhaustive CHAID Method For Owner

Sample		Classification Predicted No Go	Go	Percent Correct
Training	No Go	1457	347	80.8%
	Go	429	907	67.9%
	Overall Percentage	60.1%	39.9%	75.3%
Test	No Go	383	95	80.1%
	Go	131	251	65.7%
	Overall Percentage	59.8%	40.2%	73.7%

The result of the classification shows that the model correctly accounts for 75.3% for training sample while a slight lower percentage of 73.7% for test sample. However, the result considered acceptable and indicates that the model predicates the dependent variable with 74% correctly.

No-go categories are selected to be the target category to validate the gain, Index and Reponses plots, which reflect the model validation. The Gains chart is graphical representation of the model showing how far you need to cast the net to capture a given percentage of all the hits in the tree. The benefit of the model over randomized decision making. Gains chart for training and testing data are shown in figure 13.

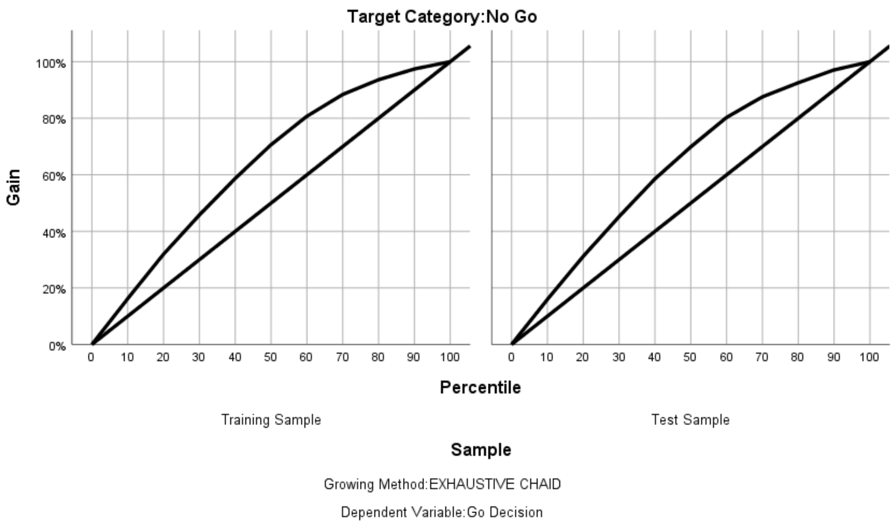

Figure 13. Gain Chart For No-Go Target Category Using Exhaustive CHAID – Owner

As it can be seen from above figure, the curve is steep closed to the threshold "diagonal line " this means gains gained are high and closed to the expected response which indicates good classifier model. The model is a good because the cumulative gains plot starts at 0% and end at 100%. Point out, the gains calculated used following equation:

$$(\text{hits in increment / total number of hits}) \times 100\%$$

Response chart for training and testing data are shown in figure 14.

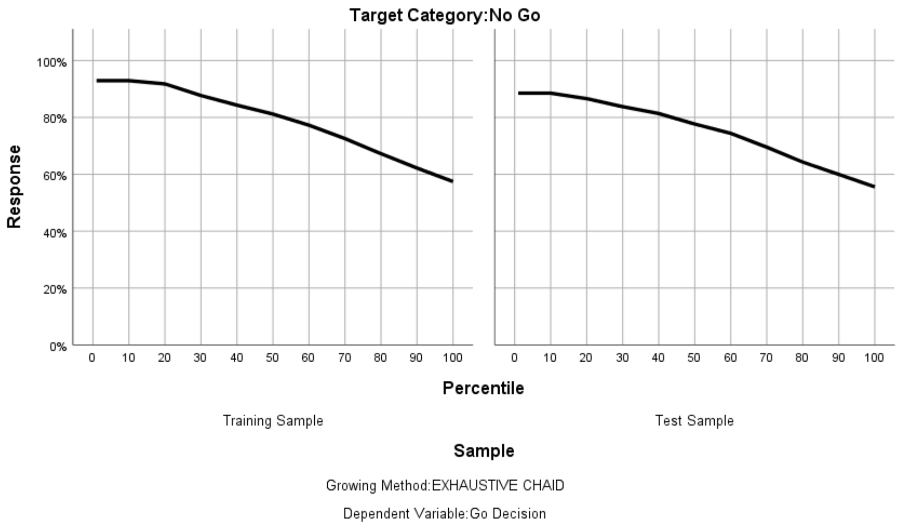

Figure 14. Response Chart For No-Go Target Category Using Exhaustive CHAID – Owner/Client

Moreover, the response chart shown in Figure 14. incites that the decision go/no-go model using Exhaustive CHAID for owner is a good model because the cumulative index chart starts above 100% and slowly descend until it reaches 100%.

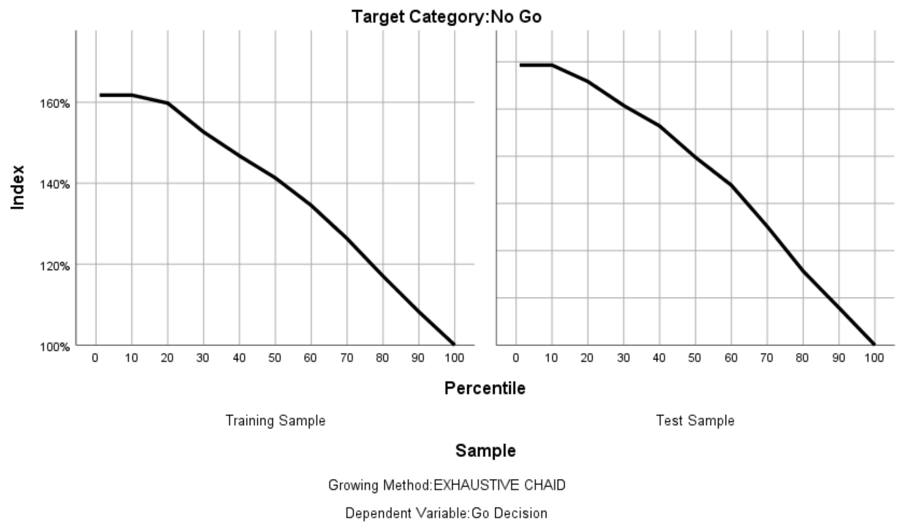

Figure 15. Index Plot For No-Go Target Category Using Exhaustive CHAID – Owner

The index chart also shows that the proposed model is a good one because the index chart always to start above 100% and descend until it reaches 100 %.

4.7.2 Using QUEST Method for Owner

The last algorithm to explore in this paper is Quick Unbiased Efficient Statistical Tree algorithm. Below table presenting the model summary:

Table 20. QUEST Model Specification

Model Summary		
Specifications	Growing Method	QUEST
	Dependent Variable	Go Decision
	Independent Variables	Organizational Risk, Project/Technical Risk, Legal Risk, Financial / Economic Risk
	Validation	Split Sample
	Maximum Tree Depth	5

Model Summary		
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	Financial / Economic Risk, Organizational Risk, Legal Risk, Project/Technical Risk
	Number of Nodes	15
	Number of Terminal Nodes	8
	Depth	4

The QUEST algorithm deal with several sequence of rules in evolution of nodes based on significant test unlike the exhaustive CHAID where the evaluation process of nodes selection is testing the category combination.

The above summary table that states the condition used in the calculation of QUEST algorithm in this model. It's divided into two sections, specification and results. Specification part gives insight about the details used to build this model. Also, the dependent and independent variables. The model predicts maximum tree depth equal to four with Minimum Cases in Parent Node equal to 100 and 50 in child node. Result part shows that total of 8 terminal nodes and total 15 nodes are presented in the model.

The visual structured model of QUEST tree-based algorithm used for the prediction of go/no go decision presented in figure 17. shows the following outcome:

- Financial / Economic Risk, Legal Risk, Project/Technical Risk, Organizational Risk are only the independent variables included.
- The modality with the highest value is the one that is highlighted with grey inside the node.
- Maximum tree depth is four which contain the most significant predictors of go/no-

go decision.

- The best predictor of go/no-go decision for owner is Financial and Economic risk similar to result in exhaustive CHAID.
- As a response variable is depicted in Figure 16, it shows node zero at the top of the constructed tree gave more than half of the prediction (57%) to not go with the project which it's financial and economic risk is high.
- In the first depth of the tree, root node was divided into two nodes since it's a binary classifier nature so only division node 1 will include (low, medium) categories while and node 2 include (High) category.
- Node 2 incite the next best predictor as legal risk level while ode 1 is terminated form tree as its outcomes is not beneficial.
- As an example of examining below tree graph, if financial/economic risk is high. The model shows 84% for no-go decision.
- In scenario where financial/economic risk is medium/Low, the model in node 2 shows that more than the half of 57% for go decision. Moving to the second predictor legal risk, if its risk is high then the model recommend for conclusion with no-go decision.
- Other scenarios can be predicted using below decision tree from root node at top to down.

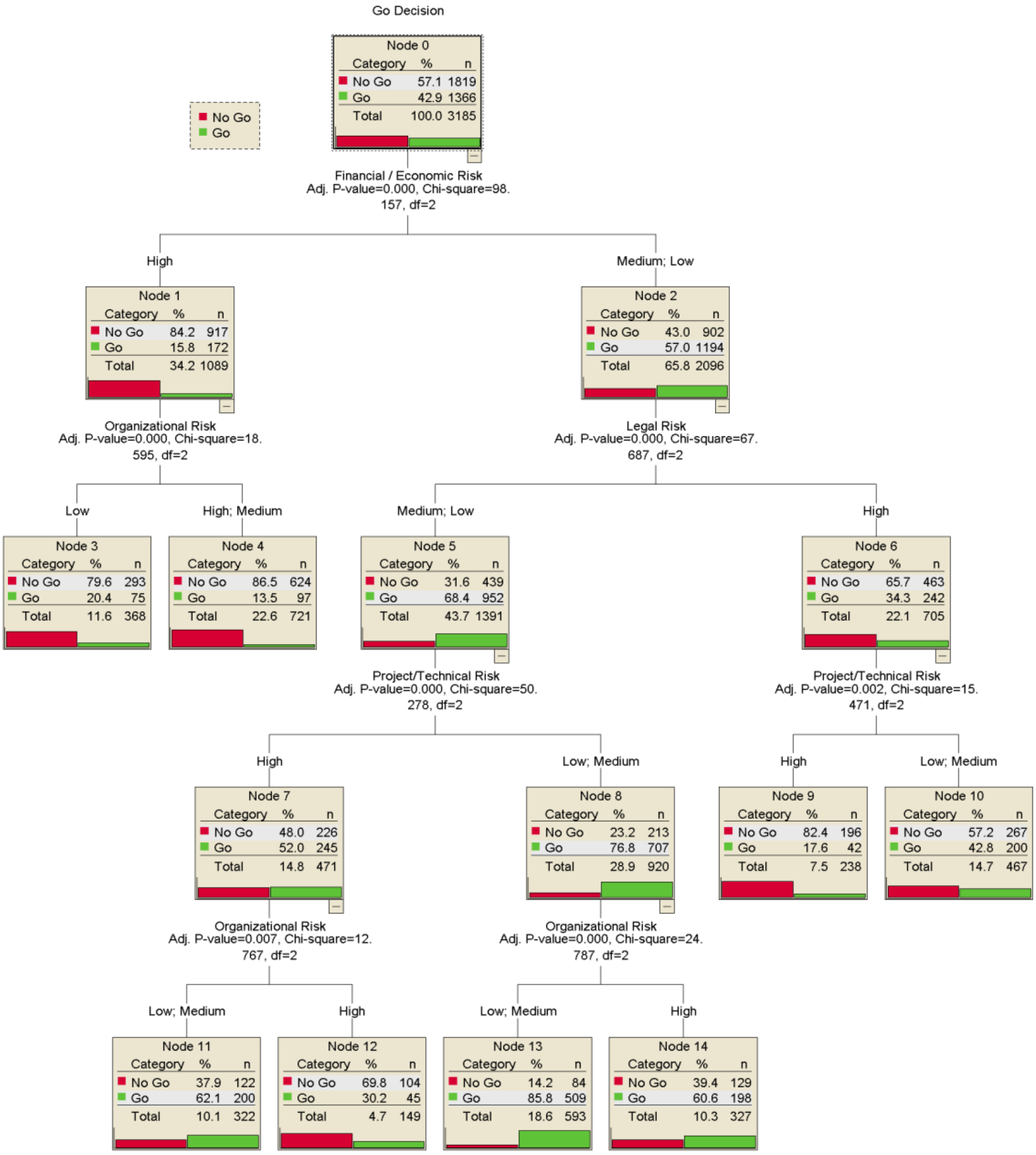

Figure 16. Decision Tree Go/No-Go Model For Owner QUEST Method

Table 21. presents the tree table for the go/no-go decision model for owner. The table tree demonstrates the structure steps of the tree diagram. It provides majority of the significant tree diagram information in a table format. For each node in the decision tree diagram, the table displays:

- The number and percentage of the go and no-go for each category.
- The parent node specified for each child node.
- The predicated category for the Go decision and the independent variables (Financial / Economic Risk, Legal Risk, Project/Technical Risk, Organizational Risk) used to divide nodes. Instance, for parent node 0, the Financial / Economic Risk has the highest Chi-square - level on the importance to the model among other categories, with two split values high and (low/medium) since its binary decision tree. For high split value, the predicated decision is no-go with 57%, and 43% is recommended to go for the project. By contrast, for low/medium Financial / Economic Risk level the predicted value is to go.
- The depth of the decision tree is four levels.

Generally, the owner or client should evaluate the 23 go/no go factors and calculated the average risk of each group. The model should be tracked from top "root node" to bottom "Child node" by decision maker. For example, it the average risk of financial and economical go/no-go factors is high and the legal risk also high, then no go decision should be considered for this project. Analysis of previous scenario as following, financial and economic risk is high (84.2% for no go) and legal risk is high too (65.7% for no-go). Another scenario for more examination of using QUEST decision tree, if financial and economic risk is low/medium (57.0% for go), and legal risk is also medium/low (68.4% for go), and project/technical risk is high (52% for go) and the last organizational should be low/medium (62% for go) while if its high the model recommend to not go with the project with percentage of almost 70%.

Generally, the decision tree model chart is more practical to be used compared to the table below. As one of the paper objectives is to create simple, quick and readable model for decision makers.

The variable with a high value of Chi-square indicates the level of importance of variable to the model; df is indicated the degree of freedom (the acceptable margin of error) for each split value. For instance, in table 21. the Financial / Economic risk group has the highest value of the Chi- Square. Therefore, it is selected as a root node of the decision tree.

Table 21. Decision Tree Table- Using Quest

Sample	No Go		Go		Total		Predicted Category	Parent Node	Primary Independent Variable				
	N	Percent	N	Percent	N	Percent			Variable	Sig.	Chi-Square	df	Split Values
0	1819	57.1%	1366	42.9%	3185	100.0%	No Go						
1	917	84.2%	172	15.8%	1089	34.2%	No Go	0	Financial / Economic Risk	0.000	98.157	2	High
2	902	43.0%	1194	57.0%	2096	65.8%	Go	0	Financial / Economic Risk	0.000	98.157	2	Medium; Low
3	293	79.6%	75	20.4%	368	11.6%	No Go	1	Organizational Risk	0.000	18.595	2	Low
4	624	86.5%	97	13.5%	721	22.6%	No Go	1	Organizational Risk	0.000	18.595	2	High; Medium
5	439	31.6%	952	68.4%	1391	43.7%	Go	2	Legal Risk	0.000	67.687	2	Medium; Low
6	463	65.7%	242	34.3%	705	22.1%	No Go	2	Legal Risk	0.000	67.687	2	High
7	226	48.0%	245	52.0%	471	14.8%	No Go	5	Project/Technical Risk	0.000	50.278	2	High
8	213	23.2%	707	76.8%	920	28.9%	Go	5	Project/Technical Risk	0.000	50.278	2	Low; Medium
9	196	82.4%	42	17.6%	238	7.5%	No Go	6	Project/Technical Risk	0.002	15.471	2	High
10	267	57.2%	200	42.8%	467	14.7%	No Go	6	Project/Technical Risk	0.002	15.471	2	Low; Medium
11	122	37.9%	200	62.1%	322	10.1%	Go	7	Organizational Risk	0.007	12.767	2	Low; Medium
12	104	69.8%	45	30.2%	149	4.7%	No Go	7	Organizational Risk	0.007	12.767	2	High
13	84	14.2%	509	85.8%	593	18.6%	Go	8	Organizational Risk	0.000	24.787	2	Low; Medium
14	129	39.4%	198	60.6%	327	10.3%	Go	8	Organizational Risk	0.000	24.787	2	High

4.7.2.1 Model validation – QUEST Method for Owner

Split-sample is an evaluation technique used in predictive decision tree models by dividing the original sample into a training set to train the model, and a test set to evaluate it. In this model, 20% of the sample size is used to measure the accuracy of the model for future cases. Also, the decision model accuracy illustrated through Gain, response and index plots as validation graphical tools.

Table 22. Risk Table - QUEST Method For Owner

Sample	Risk Estimate	Std. Error
Training	0.248	0.015
Test	0.249	0.008

According to above table, the risk estimate for the training sample is 0.248 indicates that the predicted value by the model (Go/No-Go) is wrong for 25% of the cases. In other words, the risk of misclassifying a go decision is approximately 25%. The estimated risk of the sample test is higher (24.9% of the all sample size) with a standard error of 0.008 that means the model classifying is incorrectly of around 25%.

The Risk table 23, gives the right insights about the result of classification risk estimation of model accuracy:

Table 23. Classification Table - QUEST Method For Owner

Classification				
Sample		Predicted		
		No Go	Go	Percent Correct
Training	No Go	384	79	82.9%
	Go	123	229	65.1%
	Overall Percentage	62.2%	37.8%	75.2%
Test	No Go	1484	335	81.6%
	Go	459	907	66.4%
	Overall Percentage	61.0%	39.0%	75.1%

The result of the classification shows that the model correctly accounts for 75.2% for training sample while a slight lower percentage of 75.1% for test sample. However, the result considered acceptable and indicates that the model predicates the dependent variable with 75% correctly. No-go categories are selected to be the target category to validate the gain, Index and Reponses plots, which reflect the model validation. The Gains chart is graphical representation of the model showing how far you need to cast the net to capture a given percentage of all the hits in the tree. The benefit of the model over randomized decision making. Gains chart for training and testing data are shown in figure 17.

Figure 17. Gain Chart For No-Go Target Category Using QUEST– Owner

As it can be seen from above figure, the curve is steep closed to the threshold "diagonal line " this means gains gained are high and closed to the expected response which indicates good classifier model. The model is a good because the cumulative gains plot starts at 0% and end at 100%. Point out, the gains calculated used following equation: (hits in increment / total number of hits) x 100%

Response chart for training and testing data are shown in figure 18:

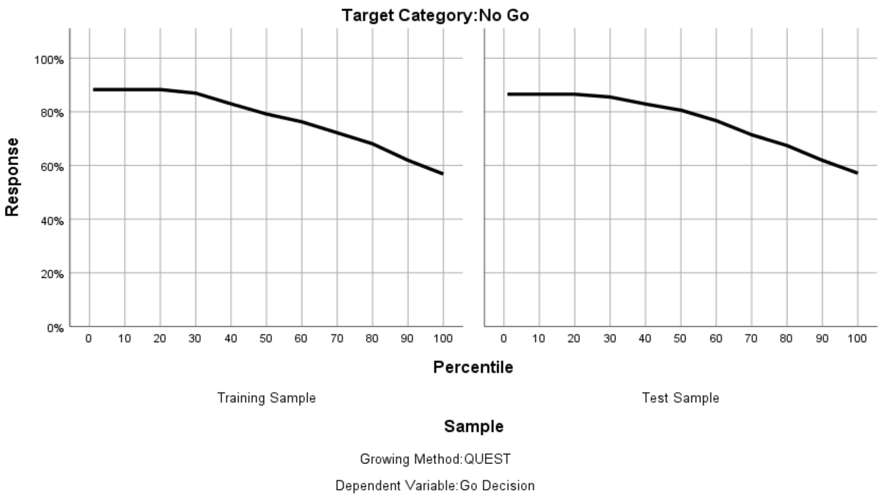

Figure 18. Response Chart for No-Go Target Category Using QUEST – Owner/Client

Moreover, the response chart shown in Figure 18. incites that the decision go/ no-go model using Exhaustive CHAID for owner is a good model because the cumulative index chart starts above 100% and slowly descend until it reaches 100%.

Figure 19. Index Plot For No-Go Target Category Using QUEST – Owner

The index chart also shows that the proposed model is a good one because the index chart always to start above 100% and descend until it reaches 100 %.

CHAPTER 5

5.1 Case study

In order to get in depth to the proposed models, a construction case study will be implemented to test the results of this model. The case is interesting as its involving owner, main contractor and governmental sector. The issue raised from the owner of famous mall which located in one corner of critical intersection in Qatar. The new design of intersection affected badly the income to the owner as its limited the visitors to the mall due to indirect way access to the mall compared to the past. The owner requests the Public Works Authority to develop direct way to his mall. In this regard, local authority took action and has engaged experience project management company to prepare conceptual design and complete evaluation study for adding the tenth bridge to be as direct connection from expressway highway landing to the mall to increase mall visitors as it was in past. Point out the work in this intersection is ongoing to develop free stopping intersection by building nine bridges for smooth traffic flow. The proposed additional bridge will be number ten which consider a challenge as its considered complex design.

5.1.1 Project description

The project includes grade-separated interchanges with crossroads, frontage roads, overpass and underpass structures, retaining walls, and all related infrastructure. The intersection considered as the most complex intersection in Qatar which include nine bridges in one area for easy traffic flow. The proposed additional bridge will serve only the mall; thus, the cost will be on owner of the mall as discussed with local authorities and mall owner to give part of parking area to construct the bridge total of 950 m2. Overall total area required to construct the additional; bridge around 1,350 m2. The additional bridge will cause removal of six existing residential building.

5.1.2 Contract type:

The proposed contract is design build assigned to the same main contractor who is working in this intersection subjected to advanced approval from mall owner.

5.1.3 Estimated Cost:

The contractor provided conceptual design for the additional bridge with total cost of 109 QR millions obligated to mall owner.

5.1.4 Project Period:

The proposed time is extremely tight as the additional bridge should not impact the completion day of ongoing project. The local authorities denied any postponing of opening day as it will lead to high impact on neighbors and local society.

5.1.5 Site description

As stated previously, the site already busy with ongoing project and additional work required more constrains and affect many activities. High level of logistics and planning to achieve the target without delaying works of remaining bridges.

5.1.6 Market condition

From mall owner perspective, the market classified as highly competitive as another two malls located at same intersection and already have direct access. The closure of direct access to his mall affected his profit and might lose the marketplace with less customers situation.

5.1.7 Design and construction

The proposed conceptual design consists of single lane bridge including MSE walls and six piers and retaining wall. A conceptual design prepared to have clear overview of buildability. The designer already designed previous nine bridges and he aggregated the tenth one in the same intersection. The proposed construction work will be assigned to the same main contractor working in the intersection as he already experienced with sequence of the work and requirement. This will minimize of unexperienced contractor and prevent mistakes.

5.1.8 Procurement:

Following materials considered the most important, Concrete, Reinforcement, Pre-stressing Strand, Concrete Cover to steel reinforcement, Surface Finishes, Waterproofing, Bearing and Expansion Joint, Deck Surface and Sub-Surface Drainage. Most of the construction material required for this project could be purchased from same suppliers dealt with previously. Similarly, with sub-contractors and equipment's used before in the ongoing project.

5.2 Risk Assessment:

Table 24. Evalustion of Risk Factors (Case Study)

GNG Risk Factors	Level of Importance on execution decision 1= Very Low, 2=Low, 3=Medium, 4=High, 5= Very High					
	Effect/Condition	**1**	**2**	**3**	**4**	**5**
Organizational Risk Factors (Owner, CM, designer, planner, contractor ...)						
1. Financial stability of owner	- The owner budget is limited				■	
2. Consultant, suppliers' reliability and experience in construction	- The team considered experience as they build 4 bridges so far.	■				
3. Design errors and omissions (Rush design)	- Rush design was not practiced in this project. - Delay in Design progress may affect the Construction works.				■	
4. Qualification of designers & planners	- The team are qualified and suitable	■				
5. Availability of skilled labors	- Skilled labors are available with some challenges		■			
6. Availability of reliable and experienced contractors	- The main contractor who assigned for this intersection has good reputation internationally. - Communications between parties are in a satisfactory manner.	■				
Project/Technical Risk Factors						
1. Availability of resources (materials & equipment)	- Most of materials & equipment will be purchased from local suppliers with few items will be ordered from outside		■			
2. Geological conditions of construction site	- Geological investigation conducted and found suitable for proposed construction	■				
3. Availability of	- Extensive technologies will be used in managing				■	

GNG Risk Factors	Level of Importance on execution decision 1= Very Low, 2=Low, 3=Medium, 4=High, 5= Very High Effect/Condition	1	2	3	4	5
construction technologies and/or skills	and execution the project				■	
4. Size and location of project	- The project may be affected through working in vicinity of Al Shamal busy Main Road and over live traffic (safety hazard) or on the road itself.					■
5. Safety level required	- The project may be affected through working in vicinity of Al Shamal busy Main Road and over live traffic (safety hazard) or on the road itself.					■
6. Complexity of the design and scope	- The design considered as complex as the additional bridges wasn't in the plan and extensive design procedure to find way for the tenth bridge without changing the ongoing main scope.					■
7. Site space constraints	- The project constrained with residential buildings surrounded and live traffic on expressway in heart of the city. - Site access is limited because of live traffic flow					■
8. Tight schedule	- The proposed project should not affect the completion day of the main scope; thus, it should be executed within the remaining one year of project finish date as instructed by local authorities.					■
Legal Risk Factors						
1. Excessive approval procedures in administrative departments	- Expected delay in approvals local authorities on proposed design. - Expected delay in Civil Defense approvals. - Expected delay in approval from Traffic Department.				■	
2. Specifications and standards required	- The team is aware of standards since they experience it already in previous 9 bridges.		■			
3. Dispute settlement procedure	- Some difficulties experienced in settlement procedure with authorities and stakeholders surrounding the limit of work.				■	
Financial and Economic Risk Factors						
1. Underestimated budgeting	The estimator experienced but unforeseen activity may arise during construction because of project complexity nature.					■
2. Inflation and deflation	Materials subjected to increase as its fast trach project.				■	
3. Price of raw materials	The material to be purchased immediately, expected high price because of short time order.				■	
4. Expected return level/Project profitability	The owner expecting to overcome his lose with the new design, so the expectation considered to be medium			■		
5. High overhead costs.	Expected to be high since the project mainly from international companies.				■	
6. Forecast about market demand / Potential level of competition	Potential of coemption considered high because of two other malls located in the same intersection. So, the need for this project is high	■				

Following the assessment of 23 go/no-go factors, an analysis to determine the categories risk level conducted and found the following conclusion can be summarized:

- Organizational Risk Factors (Owner, CM, designer, planner, contractor ...) considered as **Low risk**.
- Project/Technical Risk Factors considered as **High risk**.
- Legal Risk Factors considered as **High risk**.
- Financial and Economic Risk Factors considered as **High risk.**

5.3 Go/No-Go decision using QUEST:

Using QUEST decision tree model to predict go/no go decision presented in figure 17. and table 21, the model should be tracked from top "root node" to bottom "Child node" by decision maker.

Presented case study scenario as following, financial and economic risk is high (84.2% for no go) and legal risk is high too (65.7% for no-go), Project/Technical Risk is high (82.4% for no go). No further nodes as its not benefitable since no go decision is recommended and evaluation process should stop at this point.

5.4 Go/No-Go decision using Exhaustive CHAID:

Using Exhaustive CHAID tree model to predict go/no go decision presented in figure 13. and table 17, the model should be tracked from top "root node" to bottom "Child node" by decision maker.

Presented case study scenario as following, financial and economic risk is high (82.2% for no go) and legal risk is high too (68.5% for no-go), Project/Technical Risk is high (59.3% for no go) finally the Organizational Risk Factors is low (74.1% for no go) despite the last category has a low level of risk but the no go decision is recommended since its overall assessment prediction model.

5.5 Conclusion and discussion:

The findings obtained from the case study tested the proposed decision models ability in go/no-go decision during the early stage after conceptual design. Obviously both models resulted same conclusion for no go decision. The conclusion assists owner decision and prevent him from unwanted cost lose. The result strengthens the evaluation provided to the mall owner and the difficulties expected overall above risk factors.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This chapter summarizes overall outcome of this thesis and present conclusion. It's divided into five sections. In the first section a review on objective of this paper and highlighting the previous literatures done in this subject. Following that, summary result founded in this paper. The Third section incites the major contribution accomplished from this research. The fourth section present the research limitation. In the end, a recommendation stated for the owner and the future studies that can be added for using decision tree for go/no go models.

6.2 Review on objective and result of previous literature

As stated in chapter 1, this research aimed to identify the most significant risk factors that could stand in front owner Go/No Go decision using relative importance index and categories these factors to related influence group. The second objective is to develop decision tree for Go/No Go models for owner using QUEST and exhaustive CHAID algorithms as a decision tool in the early stage before execution. Also, to provide recommendation for owner for practical use of the model. Overall, the central focus in this paper to develop decision support system for owner considering the critical factor that affecting the failure or success of the construction project. An extensive literature has done by researcher through the existing decision support systems used in construction industry during different project cycle and identifying the key features of each model in order to add new effective simplified model by understanding the gap. Subsequently, a literature in critical factors affecting the decisions during early stage of the project from owner perspective and its risk degree.

The result of literature review can be concluded that a considerable amount of literature has been published on contractor decisions while there has been relatively little literature published on owner/ clients or construction management firm decision. Also, certain models required complicated inputs and advanced understanding of mathematics and required software to run the model, which is not practical for the owner. Additionally, some models didn't address the importance of risk assessment in early stage of the project while focusing on bidding stage despite that early stage decision is much critical decision to be considered. Moreover, some previous feasibility models exclude some factors affecting owner's decision and mainly focusing in financial factors, a combination of all expected factors will result better decision strategy for owners. Additionally, other researcher highlighted most of observed models are theoretical remained in academic circles more than being practical. Thus, emphasize the researcher to develop model with simplicity assumption that support owner's decision in early stage of the project is significantly needed.

6.3 Summary Result

Twenty-three key factors identified from the literature that should be investigated before processing the go/no go decision by owner. These factors categorized into four main groups and ranked based on relative importance index, and it was concluded that top ten five go/no-go factors are: 1) Financial stability of Owner. 2) Underestimated budgeting. 3) High overhead cost. 4) Availability (materials & equipment). 5) Consultant, Suppliers reliability and experience in construction. Obviously, Financial stability of Owner considered as the most critical risk factor in the execution decision. Thus, financial accounting and analysis will help in reporting and evaluating the financial health of the owner which can be achieved by assessing the following business factors (liquidity, activity, Profitability). Financial statement for the owner for last 5 years will be beneficial as well which can be prepare by certified consultancy. Following that, Spearman's correlation test applied to investigate the relationship between each two paired, and it was concluded that all the relationships are positive. As an example, the relation between project factors and legal factors with coefficient equal to 0.696 considered as the strongest relationship.

Subsequently, ANOVA test analysis was performed amongst a different group of respondents include company size, and company sector, project size and it can be concluded that most of the comparisons do not have a statistical difference on go/no-go groups. A slight difference in opinion found between respondent from people who are working in mega project and small project overall the legal category in regard the level of importance of “Lack of legality and standard dispute settlement procedure” factor.

In this research, two decision tree algorithms Exhaustive CHAID and QUEST go/no-go decision tree models were structured to aid the owner to have right decision during early stage process. The primary goal of using two algorithms is to study the prediction accuracy of each algorithm and percentage of errors. Starting with the accuracy of the Exhaustive CHAID go/no-go model for owner on the no-go decision that found to be around 81%, and on go decision. 65.7% with an overall accuracy of 74%. The best predictor of go/no-go decision for owner is Financial and Economic risk. Followed by legal risk, project/technical risk and finally organizational risk which ranked as the lowest according to chi-square value. The structure of Exhaustive CHAID tree consist of 28 nodes including 17 terminal nodes and maximum of three level depth.

The second algorithm was QUEST which consist of 15 nodes including 8 terminal nodes and maximum tree depth equal to four levels. The best predictor of go/no-go decision for owner is Financial and Economic risk. Followed by legal risk, project/technical risk and finally organizational risk which ranked as the lowest according to chi-square value. In terms of accuracy of QUEST model, it’s concluded that a percentage of 82% on owner on the no-go decision. While on go decision around 66.4% on owner decision. However, the overall accuracy of QUES prediction accuracy of 75.1%. Consequently, the obtained accuracy results of both models are extremely close, thus both models are highly probable to be used as prediction model because their performance performed are acceptable. In conclusion, QUEST technique proved to be more efficient and accurate than Exhaustive CHAID.

Split-sample validation technique was applied on decision tree models and gain chat, responses and index chart were demonstrated the accuracy of the go/no-go Exhaustive CHAID and QUEST models, all the charts indicated that the proposed models are good models.

6.4 Contribution of the study

The main contributions of this research can be summarized as following:

- It is the first study, which proposes using Exhaustive CHAID and QUEST decision tree algorithms to develop go/no-go decision models for owner in the construction industry that will contribute in business expansion.
- The proposed concept in this study overcomes the shortage of most previous models such as avoiding the complexity and the difficulties of applying the concept which done through extensive comprehensive literatures of previous studies conducted.
- The proposed model has main four risk groups, which are fed by 23 go/no-go factors. Most of the previous feasibility analysis or evaluation models' techniques were limited to financial factors neglecting the other factors.
- The proposed models have been statistically validated, which indicates the accuracy of the models is reasonably good.
- The proposed models are in a form of multiple effect (or variable)

analysis which allows the companies to explain, describe, predict or classify an outcome. Refereeing to de Ville (2006) that applying the multiple variables analysis is an essential in current problem-solving because critical decision and outcomes are impact by multiple factors and using concept of one-cause and one-effect relationships may lead to costly and wrong decision.

6.5 Research Limitation

The research question was achieved, and objective of this paper successfully met. However, still certain limitation in this research can be summarized as following: First, collected data for this research completed by different local companies or governmental organizational. Secondly, this research is limited to 23 risk factors identified as the most critical factors affecting go/no-go decision according to the local market. However, other factors could be more critical in other countries that gives limited perspective. The presented decision models are limited to the medium to large project where high risk level is expected.

6.6 Recommendation

The researcher would like to recommend the followings:

- Owners should conduct overall risk analysis and use understandable decision support techniques in early stage of the project to avoid any unexpected future problems.
- Proposed decision tree model will help owners and project managers in the construction industry to realize and measure the risk during the early stage of construction project and expedite them to take faster course of action.
- This stage considered as the most important project phase for the owner so it’s expected from owner to consider evaluation process is must before execution to save time and cost and unforeseen risk.

- The owner could reduce the level of risk with known contractor, so interpreting the proposed model with reliable contractor will minimize level of risk.
- Constructed decision tree with consist of four main groups, which feeds by 23 go/no go factors, aids the owners to have a concept of the targeted projects and measuring the probability of failure (no-go decision).

6.7 Future Studies

There are some futures research can be added value to this study:

- The necessary to repeat this research every five years as the market condition are changing frequently and may new risk factors have higher impact rather the one studied.
- In the absence of best practice decision support system for owner, suggested several data mining techniques that will add value to present research, such as using CRUSE and MARS algorithms to develop go/no go decision models and examine the differences with the proposed classifier used in this models.
- Several decision support tools could be employed to help owners in decision making such as, logistic regression and nearest neighbor analysis.
- Develop software algorithms based on QUEST and exhaustive CHAID growing algorithms for go/no go decision model for the owners in the construction industry.

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APPENDICE

7.1 Questionnaire Form

Master Thesis Questionnaire

Qatar University

College of Engineering

Engineering Management Master's Program

Dear Respected Participant,

This questionnaire is intended to study decision tree technique in project definition and planning stage of construction projects. The answers of this survey will be used for academic reasons and all the results will be shared with those who participated in this survey. The information provided by you is confidential. Your participation is extremely appreciated and makes this study successful. The survey will take a few minutes of your time and include three parts:

Part 1: General information about organization profile.

Part 2: Risk factors affecting execution decision.

Part 3: Scenario of Go / No Go Decision.

We highly appreciate your support for this academic study.

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Part 1: Basic Personal and Company Information

1. How many years have you worked in the construction sector?

- 1-5
- 11-15
- >21
- 6-10
- 16-20

2. Which the following describe your company sector?

- Private Owner
- Public Owner

3. Which of the following describes your company size (number of employees)?

- 1-50
- 51-100
- 101-500
- More than 500

4. Which of the following describe your company work volume in the last 5 years (USD)?

- $1 - $5 million
- $6 - $50 million
- $51 - $100 million
- $101 - $500 million
- More than $500 million

5.. At which stage of project lifecycle do you believe final go / no go decision should be performed?

- At the end of Conceptual Design
- At the end of Preliminary Engineering
- At the end of Final Design

Part 2: Risk factors affecting go/no go decision in early stage of project before execution

How important do you think the following risk factors affect go/no go decision in early stage of project before execution? (Please mark only one answer per row).

GNG Risk Factors	Level of Importance on execution decision 1= Very Low, 2=Low, 3=Medium, 4=High, 5= Very High				
	1	**2**	**3**	**4**	**5**
Organizational Risk Factors (Owner, CM, designer, planner, contractor ...)					
1. Financial stability of owner					
2. Consultant, suppliers reliability and experience in construction					
3. Design errors and omissions (Rush design)					
4. Qualification of designers & planners					
5. Availability of skilled labors					
6. Availability of reliable and experienced contractors					
Project/Technical Risk Factors					
1. Availability of resources (materials & equipment)					
2. Geological conditions of construction site					
3. Availability of construction technologies and/or skills					
4. Size and location of project					
5. Safety level required					
6. Complexity of the design and scope					
7. Site space constraints					
8. Tight schedule					
Legal Risk Factors					
1. Excessive approval procedures in administrative departments					
2. Specifications and standards required					
3. Dispute settlement procedure					
Financial and Economic Risk Factors					
1. Underestimated budgeting					
2. Inflation and deflation					
3. Price of raw materials					
4. Expected return level/Project profitability					
5. High overhead costs.					
6. Forecast about market demand / Potential level of competition					

Part 3: Scenario of Go / No Go Decision

How your company/organization takes go decisions in early stages before execution for different scenarios. Please click on Go decision (Go / No Go) below for different scenarios.

7.2 Form (A)

Scenario	Organizational Risk	Project/Technical Risk	Legal Risk Factors	Financial / Economic Risk	Go Decision	
					GO	NO GO
1	Low	High	Medium	Medium		
2	High	Low	Low	High		
3	Medium	Medium	Medium	Low		
4	High	Medium	Medium	Medium		
5	High	Low	Medium	Medium		
6	Low	Medium	High	Medium		
7	Low	Low	High	Medium		
8	Low	Medium	High	Low		
9	Low	Medium	Low	Medium		
10	High	High	Medium	Low		
11	High	High	Medium	Medium		
12	Medium	High	Medium	Low		
13	Low	Medium	High	High		
14	High	Low	Medium	High		
15	Medium	Low	High	Low		
16	Medium	Medium	Low	High		
17	Medium	Low	Low	High		
18	Medium	Medium	Medium	Medium		
19	Low	Medium	Low	Low		
20	Low	High	High	High		
21	High	Medium	High	Medium		
22	Low	Medium	Low	High		
23	High	High	High	High		
24	Medium	Low	Medium	Medium		
25	Medium	High	Low	High		
26	Low	Low	Low	Medium		
27	Medium	High	High	Low		
28	High	Low	Low	Medium		
29	Medium	Medium	High	Medium		
30	High	High	Medium	High		

Scenario	Organizational Risk	Project/Technical Risk	Legal Risk Factors	Financial / Economic Risk	Go Decision	
					GO	NO GO
31	High	High	Low	High		
32	Medium	High	Medium	High		
33	High	Medium	Low	Low		
34	Medium	Low	Medium	High		
35	Medium	High	Low	Medium		
36	Medium	Low	Low	Low		
37	High	High	Low	Low		
38	Medium	High	High	Medium		
39	High	Low	Low	Low		
40	Medium	Medium	Medium	High		

7.3 Form (B)

Scenario	Organizational Risk	Project/Technical Risk	Legal Risk Factors	Financial / Economic Risk	Go Decision	
					GO	NO GO
1	Low	Low	Medium	Low		
2	Medium	High	Medium	Medium		
3	Low	Low	High	Low		
4	Low	High	Medium	Low		
5	High	Medium	Medium	High		
6	Medium	Low	Medium	Low		
7	High	Medium	High	Low		
8	High	High	Low	Medium		
9	High	High	High	Low		
10	Medium	Medium	High	High		
11	Low	Low	Medium	Medium		
12	Medium	Medium	High	Low		
13	High	High	High	Medium		
14	Low	Low	Medium	High		
15	Low	Low	Low	High		
16	Medium	Low	High	Medium		
17	Low	High	High	Medium		
18	Medium	Medium	Low	Medium		
19	Medium	High	Low	Low		
20	Low	Low	High	High		
21	High	Low	High	Low		
22	Low	High	Medium	High		
23	Low	High	Low	Low		
24	High	Medium	Low	Medium		
25	Low	High	Low	Medium		
26	Medium	Low	High	High		

Scenario	Organizational Risk	Project/Technical Risk	Legal Risk Factors	Financial / Economic Risk	Go Decision	
					GO	NO GO
27	Medium	Low	Low	Medium		
28	Low	Low	Low	Low		
29	High	Low	High	High		
30	Low	High	High	Low		
31	High	Low	Medium	Low		
32	Low	Medium	Medium	Medium		
33	High	Medium	Low	High		
34	High	Medium	High	High		
35	High	Medium	Medium	Low		
36	Low	Medium	Medium	High		
37	Medium	High	High	High		
38	Low	High	Low	High		
39	High	Low	High	Medium		
40	Low	Medium	Medium	Low		

7.4 APPENDICE B: Detail Tables

Multiple Comparisons - Company Size

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Organizational Risk	1-50 Employee	51-100 Employee	0.2905	0.3644	0.8556	-0.6624	1.2434
		101-500 Employee	0.3464	0.3071	0.6733	-0.4566	1.1494
		More than 500 Employee	0.0795	0.2889	0.9927	-0.6758	0.8347
	51-100 Employee	1-50 Employee	-0.2905	0.3644	0.8556	-1.2434	0.6624
		101-500 Employee	0.0559	0.2687	0.9968	-0.6466	0.7584
		More than 500 Employee	-0.2110	0.2476	0.8293	-0.8583	0.4364
	101-500 Employee	1-50 Employee	-0.3464	0.3071	0.6733	-1.1494	0.4566
		51-100 Employee	-0.0559	0.2687	0.9968	-0.7584	0.6466
		More than 500 Employee	-0.2669	0.1510	0.2954	-0.6617	0.1279
	More than 500 Employee	1-50 Employee	-0.0795	0.2889	0.9927	-0.8347	0.6758
		51-100 Employee	0.2110	0.2476	0.8293	-0.4364	0.8583
		101-500 Employee	0.2669	0.1510	0.2954	-0.1279	0.6617
Project/Technical Risk	1-50 Employee	51-100 Employee	0.3893	0.3848	0.7431	-0.6169	1.3955
		101-500 Employee	0.3163	0.3243	0.7638	-0.5316	1.1642
		More than 500 Employee	0.0404	0.3050	0.9992	-0.7571	0.8379
	51-100 Employee	1-50 Employee	-0.3893	0.3848	0.7431	-1.3955	0.6169
		101-500 Employee	-0.0730	0.2837	0.9940	-0.8147	0.6688

Tukey HSD

		More than 500 Employee	-0.3489	0.2614	0.5434	-1.0325	0.3347
	101-500 Employee	1-50 Employee	-0.3163	0.3243	0.7638	-1.1642	0.5316
		51-100 Employee	0.0730	0.2837	0.9940	-0.6688	0.8147
		More than 500 Employee	-0.2759	0.1595	0.3138	-0.6928	0.1410
	More than 500 Employee	1-50 Employee	-0.0404	0.3050	0.9992	-0.8379	0.7571
		51-100 Employee	0.3489	0.2614	0.5434	-0.3347	1.0325
		101-500 Employee	0.2759	0.1595	0.3138	-0.1410	0.6928
Legal Risk	1-50 Employee	51-100 Employee	-0.2762	0.4621	0.9325	-1.4844	0.9320
		101-500 Employee	-0.7565	0.3894	0.2173	-1.7746	0.2616
		More than 500 Employee	-0.7128	0.3662	0.2159	-1.6704	0.2448
	51-100 Employee	1-50 Employee	0.2762	0.4621	0.9325	-0.9320	1.4844
		101-500 Employee	-0.4803	0.3407	0.4962	-1.3710	0.4103
		More than 500 Employee	-0.4366	0.3139	0.5081	-1.2574	0.3842
	101-500 Employee	1-50 Employee	0.7565	0.3894	0.2173	-0.2616	1.7746
		51-100 Employee	0.4803	0.3407	0.4962	-0.4103	1.3710
		More than 500 Employee	0.0437	0.1915	0.9958	-0.4569	0.5443
	More than 500 Employee	1-50 Employee	0.7128	0.3662	0.2159	-0.2448	1.6704
		51-100 Employee	0.4366	0.3139	0.5081	-0.3842	1.2574
		101-500 Employee	-0.0437	0.1915	0.9958	-0.5443	0.4569
Financial and Economic Risk	1-50 Employee	51-100 Employee	-0.0333	0.3578	0.9997	-0.9689	0.9022
		101-500 Employee	0.2348	0.3015	0.8639	-0.5536	1.0231
		More than 500 Employee	0.0205	0.2836	0.9999	-0.7210	0.7620

Tukey HSD							
	51-100 Employee	1-50 Employee	0.0333	0.3578	0.9997	-0.9022	0.9689
		101-500 Employee	0.2681	0.2638	0.7402	-0.4216	0.9578
		More than 500 Employee	0.0538	0.2431	0.9961	-0.5817	0.6894
	101-500 Employee	1-50 Employee	-0.2348	0.3015	0.8639	-1.0231	0.5536
		51-100 Employee	-0.2681	0.2638	0.7402	-0.9578	0.4216
		More than 500 Employee	-0.2143	0.1483	0.4746	-0.6019	0.1734
	More than 500 Employee	1-50 Employee	-0.0205	0.2836	0.9999	-0.7620	0.7210
		51-100 Employee	-0.0538	0.2431	0.9961	-0.6894	0.5817
		101-500 Employee	0.2143	0.1483	0.4746	-0.1734	0.6019
Total Risk	1-50 Employee	51-100 Employee	0.1665	0.2965	0.9432	-0.6087	0.9416
		101-500 Employee	0.1629	0.2498	0.9145	-0.4903	0.8162
		More than 500 Employee	-0.0528	0.2350	0.9960	-0.6672	0.5616
	51-100 Employee	1-50 Employee	-0.1665	0.2965	0.9432	-0.9416	0.6087
		101-500 Employee	-0.0035	0.2186	1.0000	-0.5750	0.5680
		More than 500 Employee	-0.2193	0.2014	0.6972	-0.7459	0.3073
	101-500 Employee	1-50 Employee	-0.1629	0.2498	0.9145	-0.8162	0.4903
		51-100 Employee	0.0035	0.2186	1.0000	-0.5680	0.5750
		More than 500 Employee	-0.2158	0.1228	0.3006	-0.5370	0.1054
	More than 500 Employee	1-50 Employee	0.0528	0.2350	0.9960	-0.5616	0.6672
		51-100 Employee	0.2193	0.2014	0.6972	-0.3073	0.7459
		101-500 Employee	0.2158	0.1228	0.3006	-0.1054	0.5370

Multiple Comparisons - Company Size

Multiple Comparisons

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Organizational Risk	Contractor	Client (Customer/Owner)	-0.2244	0.2079	0.5291	-0.7193	0.2704
		Consultant/CM	-0.0325	0.1355	0.9688	-0.3551	0.2901
	Client (Customer/Owner)	Contractor	0.2244	0.2079	0.5291	-0.2704	0.7193
		Consultant/CM	0.1919	0.2162	0.6493	-0.3226	0.7064
	Consultant/CM	Contractor	0.0325	0.1355	0.9688	-0.2901	0.3551
		Client (Customer/Owner)	-0.1919	0.2162	0.6493	-0.7064	0.3226
Project/Technical Risk	Contractor	Client (Customer/Owner)	-0.3006	0.2193	0.3601	-0.8225	0.2213
		Consultant/CM	-0.0894	0.1429	0.8064	-0.4296	0.2508
	Client (Customer/Owner)	Contractor	0.3006	0.2193	0.3601	-0.2213	0.8225
		Consultant/CM	0.2112	0.2280	0.6251	-0.3315	0.7539
	Consultant/CM	Contractor	0.0894	0.1429	0.8064	-0.2508	0.4296
		Client (Customer/Owner)	-0.2112	0.2280	0.6251	-0.7539	0.3315
Legal Risk	Contractor	Client (Customer/Owner)	-0.2733	0.2664	0.5623	-0.9073	0.3607
		Consultant/CM	-0.0250	0.1736	0.9887	-0.4383	0.3883
	Client (Customer/Owner)	Contractor	0.2733	0.2664	0.5623	-0.3607	0.9073
		Consultant/CM	0.2483	0.2770	0.6438	-0.4110	0.9076

	Consultant/CM	Contractor	0.0250	0.1736	0.9887	-0.3883	0.4383
		Client (Customer/Owner)	-0.2483	0.2770	0.6438	-0.9076	0.4110
Financial and Economic Risk	Contractor	Client (Customer/Owner)	0.1169	0.2026	0.8326	-0.3653	0.5991
		Consultant/CM	0.1413	0.1321	0.5348	-0.1730	0.4557
	Client (Customer/Owner)	Contractor	-0.1169	0.2026	0.8326	-0.5991	0.3653
		Consultant/CM	0.0244	0.2106	0.9926	-0.4770	0.5258
	Consultant/CM	Contractor	-0.1413	0.1321	0.5348	-0.4557	0.1730
		Client (Customer/Owner)	-0.0244	0.2106	0.9926	-0.5258	0.4770
Total Risk	Contractor	Client (Customer/Owner)	-0.1682	0.1692	0.5823	-0.5711	0.2346
		Consultant/CM	-0.0060	0.1103	0.9984	-0.2685	0.2566
	Client (Customer/Owner)	Contractor	0.1682	0.1692	0.5823	-0.2346	0.5711
		Consultant/CM	0.1623	0.1760	0.6276	-0.2566	0.5811
	Consultant/CM	Contractor	0.0060	0.1103	0.9984	-0.2566	0.2685
		Client (Customer/Owner)	-0.1623	0.1760	0.6276	-0.5811	0.2566

Multiple Comparisons – Project Size

Multiple Comparisons

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Organizational Risk	$1-$5 Million	$6-$50 Million	-0.2540	0.4223	0.9745	-1.4282	0.9203
		$51-$100 Million	0.0185	0.4079	1.0000	-1.1159	1.1530
		$101-$500 Million	-0.5903	0.3747	0.5168	-1.6323	0.4518
		More than $500 Million	-0.4123	0.3625	0.7863	-1.4203	0.5957
	$6-$50 Million	$1-$5 Million	0.2540	0.4223	0.9745	-0.9203	1.4282
		$51-$100 Million	0.2725	0.3084	0.9023	-0.5851	1.1300
		$101-$500 Million	-0.3363	0.2629	0.7044	-1.0673	0.3947
		More than $500 Million	-0.1583	0.2451	0.9670	-0.8398	0.5232
	$51-$100 Million	$1-$5 Million	-0.0185	0.4079	1.0000	-1.1530	1.1159
		$6-$50 Million	-0.2725	0.3084	0.9023	-1.1300	0.5851
		$101-$500 Million	-0.6088	0.2392	0.0893	-1.2739	0.0563
		More than $500 Million	-0.4308	0.2195	0.2922	-1.0412	0.1796
	$101-$500 Million	$1-$5 Million	0.5903	0.3747	0.5168	-0.4518	1.6323
		$6-$50 Million	0.3363	0.2629	0.7044	-0.3947	1.0673
		$51-$100 Million	0.6088	0.2392	0.0893	-0.0563	1.2739

		More than $500 Million	0.1780	0.1489	0.7540	-0.2361	0.5921
	More than $500 Million	$1-$5 Million	0.4123	0.3625	0.7863	-0.5957	1.4203
		$6-$50 Million	0.1583	0.2451	0.9670	-0.5232	0.8398
		$51-$100 Million	0.4308	0.2195	0.2922	-0.1796	1.0412
		$101-$500 Million	-0.1780	0.1489	0.7540	-0.5921	0.2361
Project/Technical Risk	$1-$5 Million	$6-$50 Million	-0.5298	0.4514	0.7663	-1.7850	0.7255
		$51-$100 Million	-0.3333	0.4361	0.9401	-1.5460	0.8794
		$101-$500 Million	-0.7865	0.4006	0.2919	-1.9004	0.3275
		More than $500 Million	-0.6601	0.3875	0.4367	-1.7376	0.4174
	$6-$50 Million	$1-$5 Million	0.5298	0.4514	0.7663	-0.7255	1.7850
		$51-$100 Million	0.1964	0.3296	0.9754	-0.7203	1.1131
		$101-$500 Million	-0.2567	0.2810	0.8910	-1.0381	0.5247
		More than $500 Million	-0.1303	0.2620	0.9874	-0.8589	0.5982
	$51-$100 Million	$1-$5 Million	0.3333	0.4361	0.9401	-0.8794	1.5460
		$6-$50 Million	-0.1964	0.3296	0.9754	-1.1131	0.7203
		$101-$500 Million	-0.4531	0.2557	0.3957	-1.1641	0.2579
		More than $500 Million	-0.3268	0.2346	0.6338	-0.9792	0.3257
	$101-$500 Million	$1-$5 Million	0.7865	0.4006	0.2919	-0.3275	1.9004
		$6-$50 Million	0.2567	0.2810	0.8910	-0.5247	1.0381
		$51-$100 Million	0.4531	0.2557	0.3957	-0.2579	1.1641

		More than $500 Million	0.1264	0.1592	0.9318	-0.3163	0.5690
	More than $500 Million	$1-$5 Million	0.6601	0.3875	0.4367	-0.4174	1.7376
		$6-$50 Million	0.1303	0.2620	0.9874	-0.5982	0.8589
		$51-$100 Million	0.3268	0.2346	0.6338	-0.3257	0.9792
		$101-$500 Million	-0.1264	0.1592	0.9318	-0.5690	0.3163
Legal Risk	$1-$5 Million	$6-$50 Million	-1.571428571428571*	0.5281	0.0298	-3.0401	-0.1028
		$51-$100 Million	-1.3333	0.5102	0.0760	-2.7522	0.0855
		$101-$500 Million	-1.611111111111112*	0.4687	0.0076	-2.9144	-0.3078
		More than $500 Million	-1.590643274853801*	0.4533	0.0061	-2.8513	-0.3300
	$6-$50 Million	$1-$5 Million	1.571428571428572*	0.5281	0.0298	0.1028	3.0401
		$51-$100 Million	0.2381	0.3857	0.9720	-0.8345	1.3106
		$101-$500 Million	-0.0397	0.3288	1.0000	-0.9539	0.8745
		More than $500 Million	-0.0192	0.3065	1.0000	-0.8716	0.8332
	$51-$100 Million	$1-$5 Million	1.3333	0.5102	0.0760	-0.0855	2.7522
		$6-$50 Million	-0.2381	0.3857	0.9720	-1.3106	0.8345
		$101-$500 Million	-0.2778	0.2991	0.8851	-1.1097	0.5541
		More than $500 Million	-0.2573	0.2745	0.8816	-1.0207	0.5061
	$101-$500	$1-$5 Million	1.611111111111112*	0.4687	0.0076	0.3078	2.9144

	Million	$6-$50 Million	0.0397	0.3288	1.0000	-0.8745	0.9539
		$51-$100 Million	0.2778	0.2991	0.8851	-0.5541	1.1097
		More than $500 Million	0.0205	0.1862	1.0000	-0.4974	0.5383
	More than $500 Million	$1-$5 Million	1.590643274853801*	0.4533	0.0061	0.3300	2.8513
		$6-$50 Million	0.0192	0.3065	1.0000	-0.8332	0.8716
		$51-$100 Million	0.2573	0.2745	0.8816	-0.5061	1.0207
		$101-$500 Million	-0.0205	0.1862	1.0000	-0.5383	0.4974
Financial and Economic Risk	$1-$5 Million	$6-$50 Million	0.2778	0.4246	0.9655	-0.9030	1.4585
		$51-$100 Million	0.2037	0.4102	0.9875	-0.9370	1.3444
		$101-$500 Million	0.0347	0.3768	1.0000	-1.0131	1.0825
		More than $500 Million	-0.0058	0.3645	1.0000	-1.0194	1.0077
	$6-$50 Million	$1-$5 Million	-0.2778	0.4246	0.9655	-1.4585	0.9030
		$51-$100 Million	-0.0741	0.3101	0.9993	-0.9364	0.7882
		$101-$500 Million	-0.2431	0.2643	0.8887	-0.9781	0.4919
		More than $500 Million	-0.2836	0.2464	0.7789	-0.9689	0.4017
	$51-$100 Million	$1-$5 Million	-0.2037	0.4102	0.9875	-1.3444	0.9370
		$6-$50 Million	0.0741	0.3101	0.9993	-0.7882	0.9364
		$101-$500 Million	-0.1690	0.2405	0.9554	-0.8378	0.4998
		More than $500 Million	-0.2096	0.2207	0.8766	-0.8233	0.4042
	$101-	$1-$5 Million	-0.0347	0.3768	1.0000	-1.0825	1.0131

	$500 Million	$6-$50 Million	0.2431	0.2643	0.8887	-0.4919	0.9781
		$51-$100 Million	0.1690	0.2405	0.9554	-0.4998	0.8378
		More than $500 Million	-0.0406	0.1497	0.9988	-0.4569	0.3758
	More than $500 Million	$1-$5 Million	0.0058	0.3645	1.0000	-1.0077	1.0194
		$6-$50 Million	0.2836	0.2464	0.7789	-0.4017	0.9689
		$51-$100 Million	0.2096	0.2207	0.8766	-0.4042	0.8233
		$101-$500 Million	0.0406	0.1497	0.9988	-0.3758	0.4569
Total Risk	$1-$5 Million	$6-$50 Million	-0.3830	0.3438	0.7987	-1.3390	0.5729
		$51-$100 Million	-0.2319	0.3321	0.9564	-1.1554	0.6916
		$101-$500 Million	-0.6286	0.3051	0.2458	-1.4769	0.2197
		More than $500 Million	-0.5461	0.2951	0.3510	-1.3667	0.2744
	$6-$50 Million	$1-$5 Million	0.3830	0.3438	0.7987	-0.5729	1.3390
		$51-$100 Million	0.1511	0.2510	0.9744	-0.5470	0.8493
		$101-$500 Million	-0.2456	0.2140	0.7807	-0.8407	0.3495
		More than $500 Million	-0.1631	0.1995	0.9246	-0.7179	0.3917
	$51-$100 Million	$1-$5 Million	0.2319	0.3321	0.9564	-0.6916	1.1554
		$6-$50 Million	-0.1511	0.2510	0.9744	-0.8493	0.5470
		$101-$500 Million	-0.3967	0.1947	0.2563	-0.9382	0.1447
		More than $500 Million	-0.3143	0.1787	0.4036	-0.8111	0.1826
	$101-$500	$1-$5 Million	0.6286	0.3051	0.2458	-0.2197	1.4769
		$6-$50 Million	0.2456	0.2140	0.7807	-0.3495	0.8407

	Million	$51-$100 Million	0.3967	0.1947	0.2563	-0.1447	0.9382
		More than $500 Million	0.0825	0.1212	0.9602	-0.2546	0.4196
	More than $500 Million	$1-$5 Million	0.5461	0.2951	0.3510	-0.2744	1.3667
		$6-$50 Million	0.1631	0.1995	0.9246	-0.3917	0.7179
		$51-$100 Million	0.3143	0.1787	0.4036	-0.1826	0.8111
		$101-$500 Million	-0.0825	0.1212	0.9602	-0.4196	0.2546

Multiple Comparisons – Years of Experience

Multiple Comparisons

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Organizational Risk	1-5 years	6-1- years	-0.1123	0.1989	0.9798	-0.6654	0.4407
		11-15	0.2159	0.1885	0.7820	-0.3083	0.7400
		16-20	0.2270	0.1885	0.7489	-0.2972	0.7512
		More than 20	0.1048	0.1885	0.9810	-0.4194	0.6289
	6-1- years	1-5 years	0.1123	0.1989	0.9798	-0.4407	0.6654
		11-15	0.3282	0.2375	0.6405	-0.3321	0.9885
		16-20	0.3393	0.2375	0.6107	-0.3210	0.9997
		More than 20	0.2171	0.2375	0.8908	-0.4432	0.8774
	11-15	1-5 years	-0.2159	0.1885	0.7820	-0.7400	0.3083

		6-1- years	-0.3282	0.2375	0.6405	-0.9885	0.3321
		16-20	0.0111	0.2288	1.0000	-0.6252	0.6474
		More than 20	-0.1111	0.2288	0.9885	-0.7474	0.5252
	16-20	1-5 years	-0.2270	0.1885	0.7489	-0.7512	0.2972
		6-1- years	-0.3393	0.2375	0.6107	-0.9997	0.3210
		11-15	-0.0111	0.2288	1.0000	-0.6474	0.6252
		More than 20	-0.1222	0.2288	0.9836	-0.7585	0.5141
	More than 20	1-5 years	-0.1048	0.1885	0.9810	-0.6289	0.4194
		6-1- years	-0.2171	0.2375	0.8908	-0.8774	0.4432
		11-15	0.1111	0.2288	0.9885	-0.5252	0.7474
		16-20	0.1222	0.2288	0.9836	-0.5141	0.7585
Project/Technical Risk	1-5 years	6-1- years	0.0229	0.2126	1.0000	-0.5683	0.6141
		11-15	0.1357	0.2015	0.9616	-0.4246	0.6960
		16-20	0.2357	0.2015	0.7684	-0.3246	0.7960
		More than 20	0.0774	0.2015	0.9953	-0.4829	0.6377
	6-1- years	1-5 years	-0.0229	0.2126	1.0000	-0.6141	0.5683
		11-15	0.1128	0.2538	0.9918	-0.5931	0.8187
		16-20	0.2128	0.2538	0.9179	-0.4931	0.9187
		More than 20	0.0545	0.2538	0.9995	-0.6514	0.7604
	11-15	1-5 years	-0.1357	0.2015	0.9616	-0.6960	0.4246
		6-1- years	-0.1128	0.2538	0.9918	-0.8187	0.5931
		16-20	0.1000	0.2446	0.9940	-0.5802	0.7802
		More than 20	-0.0583	0.2446	0.9993	-0.7385	0.6219
	16-20	1-5 years	-0.2357	0.2015	0.7684	-0.7960	0.3246
		6-1- years	-0.2128	0.2538	0.9179	-0.9187	0.4931

		11-15	-0.1000	0.2446	0.9940	-0.7802	0.5802
		More than 20	-0.1583	0.2446	0.9667	-0.8385	0.5219
	More than 20	1-5 years	-0.0774	0.2015	0.9953	-0.6377	0.4829
		6-1- years	-0.0545	0.2538	0.9995	-0.7604	0.6514
		11-15	0.0583	0.2446	0.9993	-0.6219	0.7385
		16-20	0.1583	0.2446	0.9667	-0.5219	0.8385
Legal Risk	1-5 years	6-1- years	-0.0934	0.2574	0.9962	-0.8091	0.6223
		11-15	0.2365	0.2439	0.8681	-0.4418	0.9148
		16-20	-0.0302	0.2439	0.9999	-0.7084	0.6481
		More than 20	0.0365	0.2439	0.9999	-0.6418	0.7148
	6-1- years	1-5 years	0.0934	0.2574	0.9962	-0.6223	0.8091
		11-15	0.3299	0.3073	0.8195	-0.5245	1.1844
		16-20	0.0632	0.3073	0.9996	-0.7912	0.9177
		More than 20	0.1299	0.3073	0.9932	-0.7245	0.9844
	11-15	1-5 years	-0.2365	0.2439	0.8681	-0.9148	0.4418
		6-1- years	-0.3299	0.3073	0.8195	-1.1844	0.5245
		16-20	-0.2667	0.2961	0.8960	-1.0900	0.5567
		More than 20	-0.2000	0.2961	0.9613	-1.0234	0.6234
	16-20	1-5 years	0.0302	0.2439	0.9999	-0.6481	0.7084
		6-1- years	-0.0632	0.3073	0.9996	-0.9177	0.7912
		11-15	0.2667	0.2961	0.8960	-0.5567	1.0900
		More than 20	0.0667	0.2961	0.9994	-0.7567	0.8900
	More than 20	1-5 years	-0.0365	0.2439	0.9999	-0.7148	0.6418
		6-1- years	-0.1299	0.3073	0.9932	-0.9844	0.7245
		11-15	0.2000	0.2961	0.9613	-0.6234	1.0234

		16-20	-0.0667	0.2961	0.9994	-0.8900	0.7567
Financial and Economic Risk	1-5 years	6-1- years	-0.3077	0.1845	0.4586	-0.8207	0.2053
		11-15	0.1667	0.1748	0.8751	-0.3195	0.6529
		16-20	-0.4667	0.1748	0.0663	-0.9529	0.0195
		More than 20	0.1111	0.1748	0.9689	-0.3751	0.5973
	6-1- years	1-5 years	0.3077	0.1845	0.4586	-0.2053	0.8207
		11-15	0.4744	0.2203	0.2065	-0.1381	1.0868
		16-20	-0.1590	0.2203	0.9510	-0.7715	0.4535
		More than 20	0.4188	0.2203	0.3237	-0.1937	1.0313
	11-15	1-5 years	-0.1667	0.1748	0.8751	-0.6529	0.3195
		6-1- years	-0.4744	0.2203	0.2065	-1.0868	0.1381
		16-20	-.633333333334*	0.2122	0.0291	-1.2235	-0.0431
		More than 20	-0.0556	0.2122	0.9989	-0.6458	0.5347
	16-20	1-5 years	0.4667	0.1748	0.0663	-0.0195	0.9529
		6-1- years	0.1590	0.2203	0.9510	-0.4535	0.7715
		11-15	.633333333334*	0.2122	0.0291	0.0431	1.2235
		More than 20	0.5778	0.2122	0.0581	-0.0124	1.1680
	More than 20	1-5 years	-0.1111	0.1748	0.9689	-0.5973	0.3751
		6-1- years	-0.4188	0.2203	0.3237	-1.0313	0.1937
		11-15	0.0556	0.2122	0.9989	-0.5347	0.6458
		16-20	-0.5778	0.2122	0.0581	-1.1680	0.0124

Total Risk	1-5 years	6-1- years	-0.1138	0.1625	0.9559	-0.5655	0.3380
		11-15	0.1778	0.1540	0.7766	-0.2503	0.6060
		16-20	0.0155	0.1540	1.0000	-0.4126	0.4437
		More than 20	0.0880	0.1540	0.9789	-0.3401	0.5161
	6-1- years	1-5 years	0.1138	0.1625	0.9559	-0.3380	0.5655
		11-15	0.2916	0.1940	0.5627	-0.2477	0.8310
		16-20	0.1293	0.1940	0.9630	-0.4100	0.6687
		More than 20	0.2018	0.1940	0.8359	-0.3376	0.7411
	11-15	1-5 years	-0.1778	0.1540	0.7766	-0.6060	0.2503
		6-1- years	-0.2916	0.1940	0.5627	-0.8310	0.2477
		16-20	-0.1623	0.1869	0.9077	-0.6821	0.3574
		More than 20	-0.0899	0.1869	0.9889	-0.6096	0.4299
	16-20	1-5 years	-0.0155	0.1540	1.0000	-0.4437	0.4126
		6-1- years	-0.1293	0.1940	0.9630	-0.6687	0.4100
		11-15	0.1623	0.1869	0.9077	-0.3574	0.6821
		More than 20	0.0725	0.1869	0.9951	-0.4473	0.5922
	More than 20	1-5 years	-0.0880	0.1540	0.9789	-0.5161	0.3401
		6-1- years	-0.2018	0.1940	0.8359	-0.7411	0.3376
		11-15	0.0899	0.1869	0.9889	-0.4299	0.6096
		16-20	-0.0725	0.1869	0.9951	-0.5922	0.4473

*. The mean difference is significant at the 0.05 level.