IMPACT OF ARCHITECT/ENGINEER (A/E) CONSULTANT QUALIFICATIONS ON PROJECT OUTCOMES

by

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ABSTRACT

The selection of Architect/Engineer (A/E) is one of the critical decisions made by owners early in a project. Driven by the presumption that architects and engineers are not commodities; hence, the assessment of A/E firms should be based on their qualifications. This research aims to study, define, and predict the impact of A/E consultant qualifications on project outcomes. It is considered one of the first attempts to quantitatively assess and understand the effects of A/E capabilities on project performance in Alberta. It helps to determine A/E qualifications and project characteristics that are correlated to project performance. A model is developed to aid owners to predict project outcomes early in the procurement stage, based on the ranking of the A/E consultant qualifications and/or project characteristics. To achieve this, the model identifies the correlations between A/E consultant qualification, project characteristics, and project outcomes, and it was furtherly validated using a prediction model developed using artificial neural networks. This model will help in eliminated the current industry practice of having unstandardized evaluation criteria to assess consultants. Also, it connects the gap between the consultant procurement decision and its impact on the management performance and outcomes of a project. Furthermore, this thesis offers an understanding of current procurement practices, as well as common evaluation criteria and their respective weights as adopted by several public owners in Alberta.

PREFACE

This thesis is an original work by Amira Eltahan. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name: "Impact of Qualifications-Based Selection of Engineering Services on Project Outcomes", No.: Pro00098198, DATE: March 12, 2020.

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CHAPTER 1. INTRODUCTION

1.1 Background and motivation

Constructions projects have been continuously increasing in complexity. Hence, the success of construction projects nowadays is contingent on numerous factors of varying criticality. The proper selection of a qualified consultant is one of these factors. Also, the performance of Architect/Engineer (A/E) consultants has been shown to influence the performance outcomes, quality, and cost of construction projects (Sporrong, 2011). This thesis is particularly interested in investigating the practices concerned with procuring consultant services, which are the vendors for architectural, professional engineering consultant services. Such procurement methods are mainly divided into three clusters: selecting the lowest fee, including, or excluding the fee of the consultant as an evaluation criterion. Lowest price has been reported as the traditional procurement approach for years, which sacrifices project performance. Now, it is more common to select a consultant based by including the fee proposal as one among many evaluation criteria. One of the major disadvantages of this approach is that the owners tend to give the same score for qualifications, so the fee is the determining factor, which could still sacrifice project performance.

In this regard, excluding the price, known as Qualifications-Based-Selection (QBS), has been promoted as a procurement method that can provide the best value of projects. The US federal government mandated through the Brooks Act that A/E consulting services be procured through QBS for all federally funded projects. As for Canadian organizations, QBS had been advocated for at national and provincial levels through the Association of Consulting Engineering Companies, Royal Architectural Institute of Canada, and others. Quebec was the first province to introduce a regulation for provincial organizations to adopt QBS. As for Alberta, major cities such as the City of Calgary have been successfully implementing QBS for about three decades.

Despite the development of multiple guides and best practices for selecting professional engineering services, several challenges inhibit the wider application of QBS. In Canada, QBS has been assessed using qualitative terms so there is a limited understanding of the set of selection criteria and qualifications to be considered during procurement. Therefore, owners questioned its validity due to the lack of studies that investigate the impact of consultant qualification on project outcomes. Additionally, methods capable of automating the selection of optimum A/E professionals for a particular project are lacking.

1.2 Research objectives and contributions

In this research, a model was developed to define, predict, and validate the impact of various A/E consultant qualifications as well as project characteristics on project outcomes. The primary objectives of the proposed research were:

1- Identify the current procurement practices adopted by big and medium sized cities in Alberta to select A/E consultant.
2- Determine criteria used for evaluating A/E qualifications during the selection process.
3- Define and evaluate the most important A/E qualifications and project characteristics that affect and predict project outcomes.

In this research, there were both academic and industrial contributions which are as follows:

Academic contributions:

1- Identified the current procurement practices to select A/E consultants as adopted by several public owners in Alberta, as well as offered an understanding of the obstacles hindering its wider adoption.
2- Presented the common evaluation criteria used to assess consultants adopted by several public owners in Alberta as captured through a set of 94 Request for Proposals (RFPs).
3- Proposed a model that highlights and provides quantitative significance between consultant qualifications, project characteristics, and project performance outcomes. The types of consultant qualifications and project characteristics that impact project outcomes are presented in this study.

Industrial contributions:

1- First application in Alberta that compares the performance of projects depending on the procurement method in place. In other words, the impact of QBS as a procurement method on project performance was compared to excluding price as an evaluation criterion. QBS projects outperformed other projects where price is included in the evaluation process.
2- A data acquisition model to find correlations and demonstrate the significance between the types of consultant qualifications, project characteristics, and project performance outcomes. This could assist owners in predicting project performance outcomes during

the procurement stage based on the consultant qualifications and project characteristics. This tool will prevent industry practices of having unstandardized evaluation criteria to assess consultants and connects the gap between the consultant procurement decision and management performance of a project.

1.3 Research methodology

To achieve the research objectives, the following was performed.

1. **Identification of current procurement practices to select A/E consultant adopted by big and medium sized cities in Alberta**

   To achieve the research first objective, a literature review, and structured interviews with 11 Alberta based municipalities were conducted. This was undertaken to capture current procurement practices and the municipalities' insights towards adopting QBS and excluding the fee as an evaluation criterion.

2. **Identification of criteria intrinsic to Canada used for evaluating A/E qualifications during the selection process**

   A set of 94 Request for Proposals (RFPs) was analyzed and sorted in a database to capture the common criteria used among the investigated sample as well as the average weight for each of the selection criteria. Also, roads and land development projects were compared in terms of the evaluation criteria, weight (%), and repetition (%). In other words, it was questioned whether the evaluation criteria would differ as the project type changes.

3. **Defining and evaluating the most important A/E qualifications and project characteristics that affect and predict project outcomes.**

   First, a questionnaire was designed to collect project data ranking A/E consultant qualification, project characteristics, and project outcomes. Then, a correlation model was developed to find the list of consultant qualifications and project characteristics that impact project outcomes using Spearman rho and Kendall tau correlation coefficients. Finally, the development of a validation model was proposed using Artificial Neural Network (ANN) and bootstrapping train the model. The output of the correlation model is an input to a prediction model using artificial neural networks to test the validity of the A/E qualifications and project characteristics in defining project outcomes. The prediction model is to be used by the Consulting Engineer of Alberta (CEA) to predict the performance outcomes of future project based on the ranking of A/E qualifications and the project characteristics. An overview of the methodology is as detailed in Figure 1.

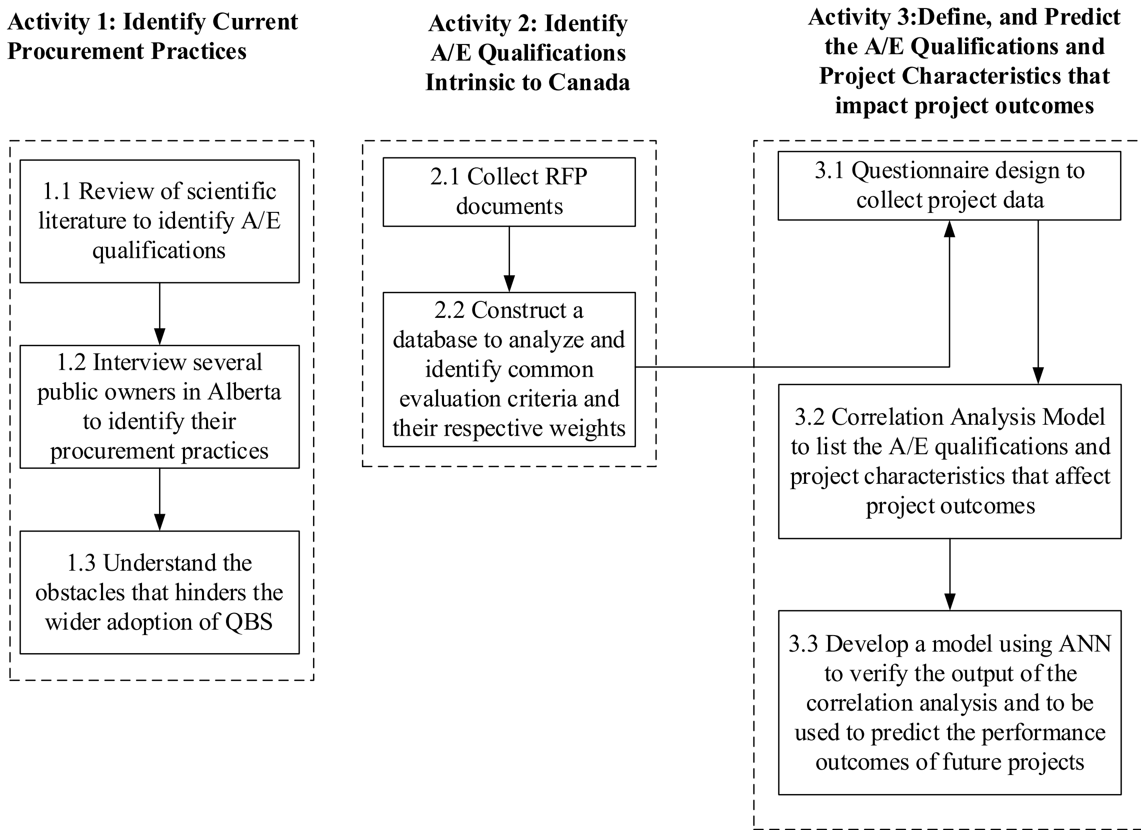

Figure 1. Methodology

1.4 Design of the study

The observations presented in this thesis are based on three research steps; the design of each is presented this section.

1.4.1 Interviewing Alberta-based Public Owners

The first stage comprises interviews with Alberta-based public owners. The purpose of this stage is to identify the current procurement practices to award A/E consultants and insights towards excluding fee as an evaluation criterion. To achieve this, a representative sample of Alberta-based public owners should be interviewed to reduce sample bias. The project is unique whereby the required data were not readily available under the research team request. In other words, the project initiators (CEA) were not the owners of the required data. Therefore, volunteer sampling was the selected approach to collect the required data, as other sampling methods automatically assume the availability of the required sample. The participants were asked to volunteer to undertake the interview; therefore, the rejection of their participation would affect the sample's representation.

The use of structured interviews was the selected approach despite requiring substantial effort and time; however, structured interviews ensure that all participants or organizations answer the questions. Structured interviews would enable the team to explain the questions to the participants and to avoid misunderstandings that can happen in questionnaires. Furthermore, structured interviews would open the roam for discussions and documents sharing.

The interviews were conducted with experts such as procurement directors or branch managers. The interviews were conducted in two rounds, meeting with different experts from the same organization in each round to ensure the generalization of the solicited data.

Selection of Participants

To diversify the sample and as an effort to achieve a representative sample the following was conducted. Participants from various governmental sectors were approached, including federal, provincial, and municipal entities. According to the Canadian Federation Taxpayers Report 2020, the municipalities within Alberta are divided into three categories. Each category varies according to the population size and annual government spending per capita. The municipalities in each category are ranked descendingly according to the annual government spending per capita($/capita). The division is as follows: big cities (population above 30,000), medium-sized municipalities (population 5,000-30,000), and small towns (population less than 5,000).

For the big cities, the report lists 14 major/big cities, and five were approached to participate in the interview. One of these participants represents above average spending/capita sector, three participants from average spending, and one low spending municipality (below average spending/capita). All the approached big cities agreed to participate in the interviews.

For the medium-sized municipalities, four municipalities were approached to solicit their participation in the interviews. The selected municipalities comprise of one high ranked municipality (above average) for spending/capita, 2 medium spending (close to average) and 1 low spending (below average). All the approached participants agreed to conduct the interview.

The small municipalities (population less than 5,000) were not included in the study given their large number and small population, and corresponding low impact on the economy and capital investment. Furthermore, three provincial governments were approached that comprise about 55% of Alberta capital investment budget for 2019 (Capital Plan 2019-23). However, only one of the approached provincial governments agreed to participate in the study. To diversify the sample in terms of the project type, one school board was approached.

To summarize, fourteen public owners in Alberta are approached and requested to volunteer in the interviewing stage of the study. The participants are from various governmental sectors and includes the following: 5 big cities, 3 provincial government, 1 federal government, 4 medium-sized municipalities, 1 school board. Out of the approached sample the following agreed to be interviewed: 5 big cities, 4 medium-sized municipalities, 1 provincial government, and 1 school board.

Challenges and Limitations

The data collection procedure is volunteer sampling therefore the rejection rate would affect the diversity of the sample. Considering this, this stage started by contacting the 14 participants, 11 of which agreed to the interview. The interviews were conducted in two rounds. During the first round, 11 interviews were conducted with the 11 public owners. Five interviews were in the second round, for a total of 16 interviews. The 11 participants comprise all the approached cities and municipalities (9 participants), 1 provincial government, and 1 school board. Therefore, the interviewed sample is missing two provincial governments and the federal government. Considering this, the current sample could be representative of several big cities and medium-sized municipalities within Alberta, but the conclusions could not be generalized to represent federal and provincial governments.

1.4.2 RFP Analysis

Originally, the interviewed owners were asked to share sample RFPs for different types of projects to be analyzed for common evaluation criteria. However, this approach was deemed unsuccessful since the participants were already volunteering to participate in the first stage.

Consequently, another approach was implemented where the CEA were asked to share some of their RFP. A set of 94 RFPs for six different public owners in Alberta were obtained. The six owners included three big cities, two medium sized cities, and one provincial government in Alberta. The project type included commercial, roads, industrial, transportation, land development and water/environmental projects. However, it should be noted that there were two types of dominant projects in the sample: land development (54% of the sample) and roads (28% of the sample).

Limitations and challenges

One of the major limitations is the generalization of the findings across Alberta since it only six public owners were included. Also, the findings could not be generalized to any type of project as majority of the sample comprised of land development and road projects. However, the results of this stage could be deemed relevant to the acquired sample and still could indicate the common trend adopted by these owners (three of the biggest cities in Alberta, as well as two medium sized cities and one provincial government) when procuring A/E consultants.

1.4.3 Questionnaire

The purpose of this stage was to design and collect the required project data to implement the proposed methodology and models. Initially, the interviewed participants were asked to share project data that relates to A/E consultant qualifications, project characteristics, and project outcomes. However, this approach was deemed unsuccessful as most of the approached owners pointed out a lack of a central share point that combines procurement and management related data. Therefore, the collection of the requested information would consume their resources. Consequently, another approach was implemented – designing a two-part questionnaire where the procurement team filled in part A and the management team will filled in part B.

The solicited data were analyzed through a two-phase methodology. The first phase was to implement feature selection to identify the list of A/E qualifications and project characteristics that relate to project outcomes. To achieve this, various feature selection methods were studied. According to literature, they are categorized into three schemes: filter, wrapper, and embedded methods. Filter feature selection was the selected approach as it runs independent of the classifier, giving more generalized results compared to the other methods. As such, similar research has been studied where filter selection was implemented. Correlation analysis was commonly found across literature to examine the significance of relationships between variables. Three different correlation coefficients (Pearson, Spearman rho, and Kendall tau) are commonly implemented. The applicability of each depends on the data type and linearity of the variables. The data solicited in this study included continuous, ordinal, and categorical data where Spearman rho and Kendall tau are applicable. Pearson is more applicable for continuous data, and it assumes linear relationship among the variables, which could not be satisfied in this study. Therefore, Kendall tau and Spearman rho were implemented, and Spearman gave better results. Considering studies of similar domain, Spearman rho was the selected correlation coefficient.

The second phase of the analysis involved building a prediction model using the list of variables obtained from the correlation model. Similar studies where project outcomes were predicted using ordinal data was evaluated. Such studies were conducted either using ANNs or ordinal logistic regression. Ordinal logistic regression can not deal with the multicollinearity between the independent variables of the dataset, which is an inherent feature of the dataset of interest. On the other hand, ANNs can deal with multicollinearity and do not require any presumption of the relationship between the variables. Therefore, ANNs were the selected classification method.

Selecting the Participants

The 14 participants who were contacted as mentioned in section 1.4.1 were asked to participate in the questionnaire. They represent several big and medium sized municipalities in Alberta and 55% of the capital investment provincial government in Alberta. Each organization was asked to provide 7–10 projects which would give a total of 98–140 projects completed throughout the last 10 years. The sample size in similar projects ranged between 33 and 40 projects. The sampling technique used is based on volunteers; thus, it imposes challenges on collecting the required number of projects.

Seven organizations agreed to take part in the surveys which would result in a total of 49–70 projects. The approached participants were asked to nominate 3–5 projects where cost was the dominant factor in selecting the A/E consultant and another 3–5 projects where the consultant qualifications were the determining factor. Also, a nomination criterion was imposed in which participants were asked to diversify the nominated projects to include various project types, sizes, and location. In case of unavailable completed projects, the intermediators were asked to provide partially completed projects.

Limitations and challenges

Four organization opted out from taking part in the questionnaire due to the unprecedented situation of COVID 19 that strained their available resources. Due to these circumstances, the initial expectations could not be met and consequently the representation of the acquired sample is affected. However, the current sample comprises 18 projects provided by three organizations. These organizations include the two major cities in the province and one small municipality. It is important to note that the proposed models are ready to be fed with new data once they are available. Therefore, a user interface was constructed to automate and facilitate the process upon the presence of a larger dataset.

1.5 Thesis Organization

This thesis includes six chapters that are organized as follows. Chapter 2 presents literature review findings that cover the procurement methods reported in literature to select A/E consultants and to identify and summarize the common A/E consultant qualifications found across literature. It also covers the methods used to predict project performance and feature selection methods used in similar studies. In Chapter 3, the results based on the RFP-analysis are presented along with the structured interviews. Chapter 4 covers the development of the correlation analysis model and case study findings based on implementing the proposed model. In Chapter 5, the output of chapter 4 is validated through a proposed prediction model the case study output is validated. Chapter 6 includes the summary of this research, limitations, and suggested future work.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This chapter includes the literature review findings related to the procurement methods used to select A/E consultants and the status of QBS adoption in Canada. Also, it presents the A/E qualifications found across literature to identify common selection criteria. Important aspects to study are the project performance evaluation indicators to be included in the questionnaire and common prediction models used in the literature to predict project performance. Eventually, correlation-based feature selection methods are also described.

2.2 Procurement Methods for selecting A/E consultant in Canada

When it comes to consultant selection methods, the owner decides which is used for a project. Various procurement processes exist for selecting a service provider, and this section summarizes the selection methods presented in the National Guide to Sustainable Municipal Infrastructure (National Research Council Canada, 2006), which was conducted by the Federation of Canadian Municipalities (FCM). There are seven selection methods presented: Request for Proposal (RFP) with Prices, Two Envelope System, Budget Method, Sole-Source, Design Competition, Price Negotiation, and Qualifications-Based Selection. In RFP and Price Negotiation, the fee of the consultant is included in the initial evaluation process to rank the bidders, and the scope of work is defined by the owner. As for the Two Envelope System, the evaluation of the consultant qualifications and expertise is assessed based on the client defined scope, and the fees are considered after the technical evaluation. In the Budget and Design Competition methods the designer has an input regarding the development of the scope of work. In the Budget method, the consultant proposes the design based on the budgeted amount specified by the owner. In the Design Competition, the consultant provides the conceptual design. All seven methods are discussed in detail below, along with the pros and cons of implementing each as described by the National Guide to Sustainable Municipal Infrastructure (National Research Council Canada, 2006)

Based on data from municipalities within Canada from the infraguide (2006), RFP and Sole Source are commonly used selection methods. Also, the average weight of the evaluation criteria assigned to price is 22%. Furthermore, the study recommended using QBS for procuring A/E consultants as the best practice. Also, a US based study showed that QBS projects are associated with lower cost overruns in comparison to other competitive procurement methods (Chinowsky and Kingsley, 2009). Such cost overruns in the QBS based project sample averaged about 3% in comparison to the 10% industry average.

2.2.1 RFP with Prices

In the RFP with Prices, the evaluation score is based on a pre-defined set of weighted evaluation criteria and is also known as best value method. The consultant is requested to submit their qualifications such as the firm's experience, key personnel, qualifications, proposed design methodology, and the proposed fee. In this method, the client gives a holistic score that combines several evaluation criteria as stated above, and the consultant ranks the firms based on such score. Since consultant selection happens at an early stage in the project life cycle, the scope is not clearly defined yet. The ambiguity of the scope in addition to including the price as an element in the evaluation criteria sacrifices the quality and the accuracy of the proposal. The mindset of the consultant will be focused on how to submit the cheapest bid rather than focusing on delivering the highest value to the owner.

2.2.2 Two Envelope System

In the Two Envelope System, the consultant is asked to submit two separately sealed envelopes. The first one is the consultant's technical proposal that includes qualifications, expertise, and proposed design, etc. The second envelope contains the consultant's financial offer. The evaluation process starts with opening the first envelope (technical proposal envelope), and the firms are ranked, accordingly. It is followed by opening the fee envelope of the highest ranked firm and negotiating their fee. If the parties do not reach an agreement, then negotiations start with the second highest firm. However, there are other practices in evaluating the Two Envelope System. Other practices include, listing the top-rated consultant where the difference in their qualification score is 5%. Thereafter, the fee proposal is opened for all this list and the consultant with the lowest fee proposal is selected.

Another evaluation technique the Two Envelope System is to award the consultant with the lowest fee proposal from the two highest ranked firms based on the technical score. Furthermore, another evaluation procedure starts with defining a cut off score for the technical proposal where firms below that cut off score are excluded. Thereafter, the fee proposals are evaluated for the passing firms where the final score is obtained through adding the score of the technical and fee evaluation and choosing the highest-ranked firm. Finally, another method for evaluating the best consultant through combining the technical and the financial offer scores through a predefined weighted percentage, also known as best value through a two-envelope submission method. For instance, some firms go for the 70-30 rule where 70 percent of the score weight would be for the technical proposal and the remaining weight would account for the fee proposal.

The Two Envelope System offers a qualification evaluation; however, like RFP it includes price in the evaluation criteria, whereas the scope is still ambiguous at such an early stage in the project. A major drawback to this method is that it enables the owners to open more than one price envelope which abuses the Two Envelope System. Such compromise changes this method to price based rather than combining the technical and fee proposal. It also leads to minimal variations in technical scores; therefore, price becomes the dominant factor.

2.2.3 Budget Method

In the Budget Method, the client sends proposal request with a predetermined budget to short listed consultants. The consultant responds with a design proposal that fits the allocated budget, and the client makes his selection based on the best value for the proposal. This method enables the client to choose the best design tailored to their budget; however, the client may miss other design options that would have long term benefit and savings.

2.2.4 Sole-Source

Other selection methods depend on previous history and working relationships between the client and the consultant, such as the Sole-Source selection method. In Sole-Source selection the designer is selected for a period such as one or two years where the consultant is asked to undertake the clients' projects. This selection procedure overcomes the drawback of having an ambiguous scope and basing the price on an unclear basis that would lead to cost overruns and change orders at later stages. However, it is suitable for small projects and specialized trades and services.

2.2.5 Design Competition

In the Design Competition Method, a group of pre-qualified consultants are asked to submit their concept design, an estimate of the construction costs, and their fee proposal. The client chooses the consultant based on their submission and the most applicable design. This selection procedure can expensive, as the client pays the concept design fee for all the competing consultants; thus, it can be applicable only on large scale projects such as museums where concept design is of an essence to the project nature.

2.2.6 Price Negotiation

In the Price Negotiation method, the proposal is sent to a prequalified list of consultants where the design fees are negotiated independently. The contract award is given to the firm with the lowest negotiated design fee. This procurement method scarifies the quality of the design as it forces the firms to lower their fee to get the project. Consequently, most reputable firms do not contribute to project where Price Negotiation method is in use as it risks their standards.

2.2.7 Qualifications-Based Selection

A QBS procedure depends on selecting the service provider based on qualifications rather than price. The performance of a design consultant has been shown to impact the cost and quality of facilities (Sporrong, 2011). In the US, QBS is mandated as the federal procurement process for public projects, and it is adopted by 47 state governments. QBS is divided into three stages as follows. The first stage includes submitting the Request for Qualifications (RFQ) and ranking the firms accordingly. Thereafter, in the second stage the highest ranked firm and the owner develop the scope of work. Once the scope of work is agreed upon, the consultant is then requested to submit the fee proposal as the third stage. If the owner accepts the fee proposal, the consultant is awarded the project. However, if an agreement is not reached the owner starts negotiating with the consultant to reach an acceptable fee. If an agreement can is not reached with the highest ranked consultant, negotiations start with the second ranked firm. One of the major advantages of QBS is that the scope of work is jointly developed with the owner. This will lead to long term benefits such as reduced change orders and cost overruns. Furthermore, QBS ensures the quality of the delivered design and enables the owner and the consultant to reach an understanding of each others needs, goals, risk tolerance, etc. According to the infraguide report there were not any reported disadvantages associated with QBS.

A study conducted by (Christodoulou et al., 2004) investigated the drawbacks and merits of QBS and compared it to traditional bidding where price is considered. It concluded that cost savings that might result due to applying traditional bidding method would be considered insignificant compared to the cost overruns that occurs in the construction phase. In other words, the author related cost overruns during the construction phase to the procurement method used to select an A/E consultant. Projects where QBS was applied are less likely to experience cost overruns during construction phase if compared to projects where traditional bidding is applied. The study was based on information from the New York City's Mayor's Office of Contracts which consisted of 162 A/E contract awards in New York City. The study divided the projects based on the work type: inspection, design services bid, design services not bid, non-professional services, and sole source. This paper concluded that QBS has advantages compared to other traditional bidding methods and should be selected for A/E services procurement procedure.

In another study conducted by Alleman et al (2017) where he compared the QBS and Best Value (BV) approach in several Construction Manager-General Contractor (CM-GC) projects. The data from this study were collected from several projects through interviews and surveys to investigate the significance of using QBS and BV procurement methods on project outcome. This paper suggests that companies tend to select BV procurement method if they are new to the market as BV is like the traditional bidding method. However, well established companies tend to use QBS in their procurement procedure due to the lack of information due to early design stage which leads to assumptions and risks which would eventually lead to an unreliable price. The difference between CM-GC and design-bid-build approach is that during CM-GC the contract is procured at the start of the project so that the contractor helps with the design phase (pre-construction phase). The research concluded that even though BV showed complicated decision-making process without significant decrease in project risk, firms still prefer using BV procurement procedure than using QBS.

QBS can lead to billions of dollars savings. For example, when traditional bidding was applied for a consultant response to an RFP with detailed proposal for $ 50,000 fees it took them $ 20,000 of their time to respond to such RFP (Harrison, 2018). Furthermore, more than one firm responds to an RFP; therefore, the total amount of money spent by firms to respond to RFPs can exceed the contract value and can even exceed the construction cost, depending on the number of firms responding to the RFP. This inefficient RFP process affects the economy of the country; therefore, QBS is a solution for that process as it can save the time and money spent by several firms to respond to the RFP (Harrison, 2018).

Project lifecycle cost is divided into construction, engineering, and operations and maintenance (O&M) costs. According to several studies, engineering/design fees represent about 1 to 2 percent of the project life cycle cost; construction accounts for 6 to 18 percent; and the remaining percentage goes for the O&M cost. In selecting professional consultant, it is essential to differentiate between cost and value of the construction project. Value reflects the savings throughout the lifetime of the project, whereas cost refers to the consultant fees. Therefore, value is more of a concern when it comes to selecting a professional consultant. In other words, design cost savings are insignificant to the project life cycle cost. However, investing in an efficient design would lead to a reduction in O&M cost, which has more significance on the project life cycle cost; thus, it will lead to more cost savings. Similarly, consultant fee reduction would sacrifice an efficient design and lead to an increase in O&M cost. In other words, design fee reductions lead to insignificant cost savings and a higher project life cycle cost. Long term savings through selecting the most qualified, experienced, highly skilled consultant outweigh the savings resulting from lowest bid designer selection (Chinowsky and Kingsley, 2009). A national study conducted by the American Council of Engineering Companies found that even though price-based selection method resulted in a lower initial consultant fee, the savings were lost due to change orders and time delays (Chinowsky and Kingsley, 2009).

2.3 QBS adoption in Canada

Based on the above literature findings, QBS had been suggested as the best practice for procuring A/E consultants. Furthermore, including price as an evaluation factor has been shown to influence the technical evaluation of consultants as owners tend to give it the same score for qualifications; thus, the fee is the determining factor, which could sacrifice project performance. Regardless of such findings, RFP and Sole Source are still the most adopted procurement methods in Canada (National Research Council Canada, 2006). Considering this, the section presents the current state of QBS adoption across Canada as reported in literature.

QBS has been advocated for at a national and provincial level in Canada. Quebec is the first province to advocate for QBS adoption though a regulation that obliges provincial institutions to use QBS when procuring consulting A/E services (Williams, 2008). In British Columbia, the cities of Coquitlam and Nanaimo regularly use QBS to procure A/E consultant services (ACEC-BC, 2016). This allows for collaboration in the design phase between the owners and the engineers; consequently, leading to a clearer scope definition. Furthermore, City of Coquitlam has been awarded the ACEC-BC Client of the Year Award for setting an excellent example for valuing professional services through adopting QBS for A/E consultant selection (Client of the Year Award, 2018). The city advocates for QBS as they believe that it has benefits in terms of project outcomes, innovation, cost control and overall satisfaction (Association of Consulting Engineering Companies-British Columbia (ACEC-BC), 2016).

In Winnipeg, a decision was taken back in 2016 to change the selection method for A/E services from lowest price to combining price and qualifications, known as Best Value Procurement (BVP), as a step towards implementing QBS (Harrison, 2016). Though BVP has its drawbacks as reported in section 2.2, including qualifications could be considered a move in the direction of adopting QBS. Also, a transit agency based in Ontario implemented QBS for two pilot projects based on discussions with the Consulting Engineers of Ontario (Lee, 2015). Also, it was noted that the agency would become open to deliver more QBS-projects due to the positive results associated with their decision.

In Alberta, preparation for introducing QBS has started in 2014 (Hixson, 2014).This came as a result of the effort by the Consulting Engineers of Alberta and the engineering industry. The City of Calgary has been successfully implementing QBS for almost 30 years and might help with the legislation of QBS in Alberta (Shelton, 2018). In this study, the current state of QBS as adopted by other cities within Alberta is presented, as well as the procurement practices currently in place.

Federal organizations such as Public Services and Procurement Canada has initiated a trial of QBS in several pilot projects in 2018 (Beyond Referrals, 2018). The purpose of such initiative is to evaluate the impact of QBS on project outcomes as well as innovation and cost savings. It could be considered a major step towards legislating QBS at a national level (Shelton, 2018).

Some large Canadian organizations have also advocated for the use of QBS, including the Association of Consulting Engineers of Quebec and the Association of Architects in Private Practice of Quebec (AAPPQ) (Shelton, 2018). Other Canadian organizations that advocate for QBS as reported by Shelton, 2018 include: Alberta Association of Architects, Association of

Consulting Engineering Companies in Canada, Alberta, British Columbia, New Brunswick, Nova Scotia, Ontario, and Saskatchewan. Furthermore, other organizations include the federation of Canadian municipalities, the Canadian construction Association (Gilbert, 2010), the Canadian Association of Management Consultants, the royal Architectural Institute of Canada, and the Ontario Association of Architects (Dreessen, 2016).

2.4 Identifying A/E Qualifications Across the Literature

This section presents the literature review findings of evaluation criteria commonly used to access consultants. The objective is to understand the evaluation criteria used.

To investigate the most influential technical evaluation criteria on project outcomes, Doloi (2009) examined the relationship between 43 technical pre-qualification criteria and project performance. After conducting structured surveys, seven attributes were found to be the most influential on contractors' performance and project success in terms of time, cost, and quality. These attributes include business stability, planning and control, quality management, past experience, risk management, organizational capability, and commitment and dedication. Moreover, further analysis was conducted that showed that technical experience, number of years of experience, working capital, and past success also have a significant impact on project's performance in terms of time, cost, and quality (Doloi, 2009).

Cheung et. al (2002) conducted a questionnaire survey to identify the common criteria for architect's selection and their role to achieve an objective selection. These criteria are the firm's background, past performance, capacity to accomplish the work, project approach, previous working relationship with the client, innovative design, ownership of the project, and staff assignments (Cheung et al., 2002).

Furthermore, Day (1998) suggested some criteria that should be used by school systems to select the competent architect for the project. These criteria include technical qualifications, experience with similar projects, and reputation with existing client, current workload, performance- incentive fee, and compatibility (W. Day, 1998).

Day and Barksdale 2003 investigated ways to assess competing professional service providers based on intangible attributes. Pressman (1995) stated that:

"As part of the architect selection process, clients should weigh the 'Chemistry' factor heavily."

Whereas the authors suggested that such factors can be assessed through the presentation/interview stage during the selection process (Pressman, 1995). The interview/presentation stage is usually performed for the shortlisted consultants where most of the competitors are considered equally qualified. Therefore, the most important criteria that are assessed during the interview stage according to the survey responses are capability, chemistry, and client orientation. The conducted survey also highlighted participants that lacked capability, showed ignorance of the local situation, lacked detail, technical error in specifying material/procedure. Furthermore, chemistry was evaluated through the chemistry and coherence between the project team, key team members presence during the presentation/interview and understanding the client's needs (Day and Barksdale, 2003).

Furthermore, another survey study proposed the following criteria to measure the qualifications of design consultants: experience (specially on comparable projects), understanding of project, and change order history. Furthermore, trust and commitment were one of the major requirements stated by owners. The criteria were divided into "hard" and "soft" criteria; hard criteria can be identified as prior experience and past performance, whereas the soft criteria include enthusiasm and responsiveness.

Day and Barksdale (2003) suggested the following criteria based on input from buyers of architecture and engineering services:

1. Past Experience
2. Understanding client's needs
3. Relationship with the client; and
4. Conforming to regulations and requirements.

The division suggested by Puri and Tiwari (2014) was similar to that of Hunt et al. (1966), where the latter divided evaluation criteria into four main groups: general, technical, managerial, and financial (Puri and Tiwari, 2014; Hunt et al., 1966). Merna and Smith (1990) proposed other groups including financial stability, managerial capability; organizational strength, technical expertise, and experience in similar projects. Moselhi and Martinelli (1990) proposed adding relevance of experience and size of firm to the groups. This study investigated constructors' selection; however, it was deemed applicable for design consultant.

Palaneeswaran and Kumaraswamy (2001) proposed the following groups of criteria: (1) Proposal Completeness and complying with requirements; (2) Promptness; (3) Obeying laws and regulations; (4) Resource capacity and current workload.

Moreover, Abdelrahman et al. (2008) determined the evaluation criteria of best value through literature, meetings, surveys and case studies. The authors summarized these findings by dividing them into four levels including parameters, evaluation criteria, subfactors, and proposed measures. The parameters include cost, time, qualification, performance, quality, and design alternatives. The evaluation criteria for these parameters include initial capital cost, life cycle cost, time for completion, prequalification, past performance, project management plan, personal experience, quality management plan, quality parameters, environmental considerations, proposed design alternates, and technical proposal responsiveness.

Lo and Yan (2009) conducted a study in which they compared contractors' bidding performance. They investigated the history of contractors' performance by including "beyond-contractual reward" (BCR) in contractor's technical evaluation. BCR can result in abnormally low bids as contractors deliberately cut their bids and consider gaining profit through BCR by submitting change orders and claims. Two simulation scenarios for contractors were investigated; the first scenario was for a contractor that had a competitive advantage in qualifications, which would result in an increased financial offer. The second scenario was for a contractor that had a competitive disadvantage in their technical evaluation in comparison to other bidders. In such cases, the contractor would resort to deliberately cut its price offer and plan to gain profit through BCR. Therefore, the author recommended including BCR and contractors' past performance in technical evaluation to force contractors to submit quality products and limit their opportunistic bidding behaviour. Even though the above study was proposed to evaluate contractor's proposal and competence, it is applicable in evaluating consultants. The design consultant usually estimates the fee while the scope of the work is not yet clearly identified; therefore, change orders occurs. Furthermore, the research team suggests adding BCR from the contractor side for projects performed by the consultant. This suggestion is to include the performance of projects delivered by the consultant. While the consultant might not be the sole reason for construction change orders, an average number of change orders across previous projects can be an adequate measure for consultant's experience.

Additionally, (Cheung, et al., 2002) conducted a survey-based study in Hong Kong where it summarized the selection criteria used by 10 different organizations: firm's background, past performance, capacity to accomplish the work, and project approach. The firm's background is divided into reputation, technical competence/qualification, and experience with similar projects. Past performance is measured through cost control, quality of work, and time control. Capacity to accomplish the work is defined by present workload, availability of qualified personnel, and professional qualification. Furthermore, project approach is assessed by the approached to time schedule, approaches to quality, and design approach/methodology.

Based on the above the following can be concluded as the commonly adopted selection criteria found in literature as shown in Figure 2.

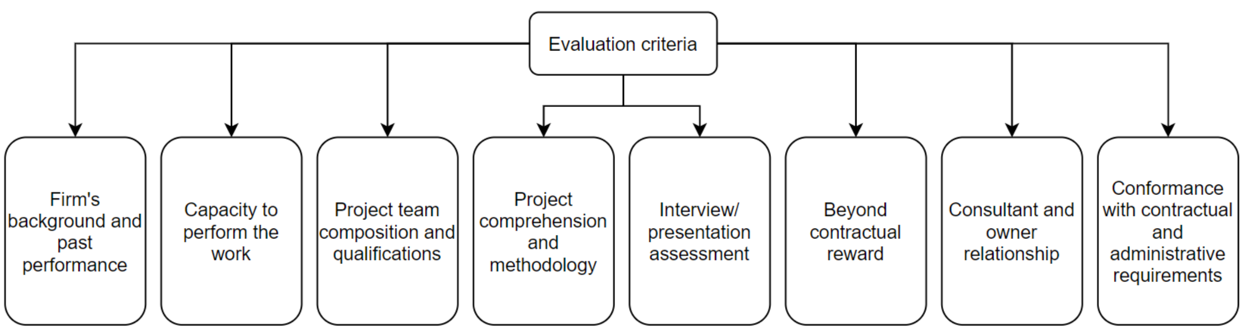

Figure 2. Evaluation Criteria as per literature

2.5 Project Performance Evaluation

When it comes to defining project success, one should discriminate between two distinctive elements of project success: product success and project management success (Baccarini, 1999). Project management success is concerned with the project process such as cost, time, and quality. Product success is more about the effect of the final product; in other words, it is concerned whether the final product meets the organizational and or customer satisfaction. Moreover, Bacarini introduced Logical Framework Method (LFM) where success is defined to the degree of achieving the project objectives. LFM consists of four main objectives, which are goal, purpose, outputs, and inputs. Product success is monitored through achieving the project goals and purpose, and the project management success is identified through project outputs and inputs. Project outputs can be easily measured as they are the intermediate tangible results, whereas the project inputs represent the management process such as budgeting, resources, etc. (Baccarini,1999).

Regarding defining project management success there are three key factors that were common in literature: meeting time, cost, and quality objectives (Ling et al., 2008; Morris and Hough, 1987; Pinto and Slevin, 1997; Turner, 1993); quality of the management process; and satisfying project stakeholders where they relate to the project management process.

Time success is measured relative to the project's initial plan; and the cost success is measured similarly (Might and Fischer, 1985). The quality of the management process is concerned with the efficiency of managing the project. Examples of measuring the quality of the managing process include number of scope changes and change orders, absence of post project problems, identifying technical problems and the ability to resolve them.

Project success is a perceptual element, like quality, which changes with stakeholder's perspective (Bannerman, 2008). Paul Bannerman (2008) described a framework that defines project success with five levels: process success, project management success, product success, business success, and strategic success. Other authors proposed including customer and project team, in addition to time, cost, and project control (Bryde and Wright, 2007). Project management success is measured through time, budget, scope, and quality. However, these elements constitute the conventional approach in determining project success which have major limitations perspective (Bannerman, 2008). This limitation lies in confining project success in the process of delivering the project rather than the end-product. In other words, our focus lies in assessing the process to deliver the project regardless of the product. Product can be assessed through the stakeholders' satisfaction with the project outcomes. For example, a project that is on budget and on schedule does not constitute a benefit to stakeholders if it does not meet the purpose it was intended for. Even though, such project can be considered successful in terms of fulfilling the project management process success factors, but it cannot be considered successful in other levels such as the business success, process success, and strategic success (Shenhar et al., 2001).

In an approach to quantify project success, Nassar and AbouRizk (2014) proposed a methodology that enables project managers to quantify project success factors throughout any phase of the project. The methodology determined a project Performance Index (PI) through quantifying eight indices: billing performance, schedule performance, profitability performance, cost performance, quality performance, safety performance, client satisfaction and project team satisfaction. After identifying the values of the eight indexes, the PI is obtained by summing the index values after multiplying them by their respective priority weights. To get the weight of the indices, the Analytical Hierarchy Process (AHP) is used, where these weights indicate the degree of sensitivity of the overall performance to each of the eight indexes. This methodology proposed a technique to integrate tangible and nontangible success factors such as client and project team satisfaction instead of relying on the traditional success factors such as time and cost. However, since the priority weights are based on expert opinion, it is considered a limitation that methodology relies on a subjective process. Moreover, the accuracy of the results depends on the accuracy of the collected data (Nassar and AbouRizk, 2014). One of the performance measures suggested in literature was the claims and disputes as an indicator for cost performance (Ling et al., 2008).

According to Eriksson and Westerberg (2011), project success should be assessed through factors other than cost, time, and quality which focus on short term aspects of project performance. Long term success factors that would ensure competitive advantage and sustainable development are as follows: environmental impact, work environment, and innovation. The construction industry is considered one of the major causes of environmental problems; therefore, it is a crucial matter to include environmental measures in project success criteria (Eriksson and Westerberg, 2011). Sustainability of projects can be achieved through energy efficient systems, using green materials, reducing construction waste, and delivering an eco-friendly project. As for work environment, health and safety has been always a critical issue and a major concern in the construction industry. The construction industry is affiliated with high risks of safety incidents. Safety incidents cause physical harms and traumas to labor and have huge effects on the economy as insurance companies must compensate injured laborers. Moreover, labor productivity dramatically declines after the occurrence of a safety incident and/or a fatality; therefore, the project suffers delays and cost overruns. Monitoring a projects' number of fatalities, recordable incidents, near miss, and sick leave days is an important factor in determining project success as proposed by Nassar and AbouRizk in 2014.

Innovation should be monitored and measured throughout the project life cycle, as for example, having an innovative design and using innovative construction methods and materials (Enshassi et al., 2009). Innovation can be applied throughout the process and to the final product itself. For process innovation, it can be implemented through having an innovative design where cost savings can be achieved (Shields et al., 2003). Also, using new technologies and construction method can be of add huge value to the project. Product innovation can be achieved through using new materials that would add value to the final product. Innovation does not necessarily means having a cheaper option; however, investing more money in an innovative process and/or product has a long-term benefit, and its saving would eventually exceed the savings incurred from implementing a non innovative process and/or process.

2.6 Feature Selection Methods

One of the applied methods in this research was feature selection, which is used to identify the variables (project characteristics and A/E consultant qualifications) that are associated with the project performance. Feature selection helps to select the input variables that are most relevant to the output variable of interest (Chumerin and Van Hulle, 2006). It creates a subset of features to be used for the learning process of the algorithm (Ladha and Deepa, 2011). Of the advantages reported with feature selection is its ability to improve the data quality and to remove redundancy and noisy data as well as performance improvement related to the prediction accuracy (Ladha and Deepa, 2011). There are two approaches in feature selection – either forward selection or backward elimination (Ladha and Deepa, 2011). In forward selection, the algorithm starts with no variables, then it adds one variable at a time where the one that contributes to the least error is selected; the algorithm is terminated a soon as adding variables does not significantly decrease the error (Wah et al., 2018). In backward elimination the algorithm starts by adding all the variables at once and them eliminates each one at a time where the eliminated variable is selected based on the variable that contribute to the highest error (Ladha and Deepa, 2011). According to literature, various feature selection methods exist, including principal component analysis (PCA), non-linear principal component analysis, correlation coefficient, independent component analysis, and correlation based feature selection (Khalid et al., 2014).

Feature selection methods are categorized into filter methods, wrapper methods, and embedded/hybrid methods ((Khalid et al., 2014; Ladha and Deepa, 2011; Li et al., 2018; Naqvi, 2012). The filter methods are independent of the used classifier. They include methods such as the correlation coefficients and minimum redundancy-maximum relevance (MRMR) (Ladha and Deepa, 2011). Wrapper methods include the classifier as a dependent factor to identify the subset feature based on the classifier prediction capability (Wah et al., 2018). Wrapper methods that are based on support vector machines (SVMs) as classifiers are commonly used in machine learning (Saeys et al., 2007; Wah et al., 2018). They also apply searching techniques like sequential forward selection (SFS) and sequential backward selection (SBS), also known as sequential backward elimination (SBE) (Wah et al, 2018), plus-1-take-away-r, and sequential floating forward and backward selection (SFFS and SFBS) (Yusta, 2009). Hybrid/embedded methods combine both filters and wrappers methods (Bolón-Canedo et al., 2013; Khalid et al., 2014; Naqvi, 2012). They also include decision trees, support vector machine recursive feature elimination (SVM-RFE) (Guyon et al., 2002) and kernel-penalized SVM (Maldonado et al., 2011).

Correlation-based Feature Selection

Filter methods are more applicable for this research since it runs independently of the classifier as mentioned before. Also, it works as a preprocessing step of the data regardless of the performance of the classifier, which gives more generalized results in comparison to wrapper methods (Sánchez-Maroño et al., 2007). Based on this, filter method was studied, which includes correlation-based feature selection. It is crucial to mention that correlation does not imply causation (Akoglu, 2018).

Correlation analysis (CA) was used in a similar study conducted by (Ling and Liu, 2004) in Singapore where they tried to find the factors that affected 11 projects performance metrics based on 33 Design Build (DB) projects (data was obtained through a survey). Also, in nursing research, correlation is a common analysis performed to examine the magnitude and the significance of the relationships between variables (Prematunga, 2012). Furthermore, CA can measure the intensity of the associations between random variables and is completely symmetrical. In other words, if A is an independent variable and B is a dependant variable, the correlation between A and B is the same as the correlation between B and A, unlike linear regression. The correlation coefficient ranges between -1 and +1. Monotonic relationship can either indicate a positive or negative trend between variables. Negative correlation indicates that as one variable increases, the other variable decreases as shown in Figure 3 (Laerd Statistics, 2020). Positive correlation indicates that the variables move in the same direction as shown in Figure as shown in Figure 4 (Laerd Statistics, 2020). Zero correlation indicates that there is a weak relationship between the variables as shown in Figure 5 (Laerd Statistics, 2020). The evaluation process intends to search for the subset of feature that are highly correlated to the dependent variables. Bivariate correlation coefficients will be discussed in the sections, including Pearson, Spearman, and Kendall correlation coefficients. The most used correlation coefficient to measure the magnitude of the correlation between interval and ratio variables is the Pearson product-moment (Pearson’s r^2) (Prematunga, 2012). The most comment tests for ordinal ranked variables are Spearman’s rank-order, also known as Spearman’s rho, or as Kendall tau-a (Prematunga, 2012). The relationship between nominal variables can be tested using Pearson’s chi-square with phi coefficient or Cramer’s V. According to the literature, Kendall’s and Spearman’s can be used to find correlations between ordinal data (scaled data type) and interval data (continuous) (Prematunga, 2012).

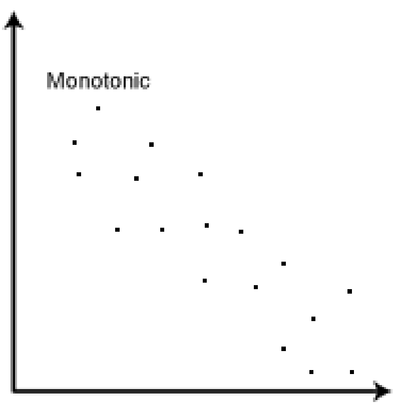

Figure 3. Negative Correlation

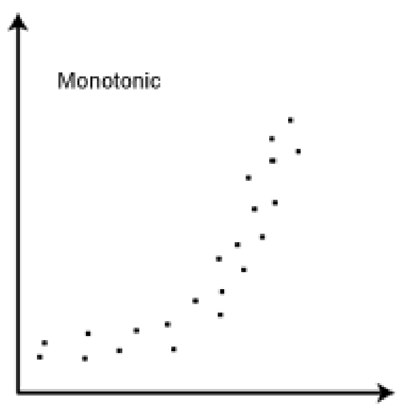

Figure 4. Positive Correlation

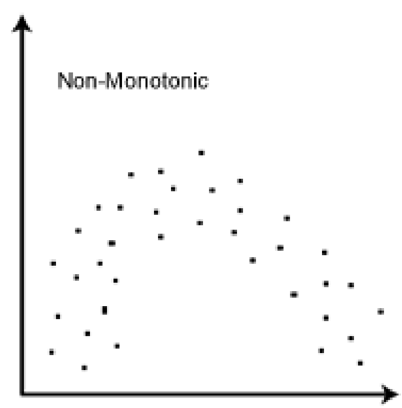

Figure 5. Zero Correlation

Pearson Correlation Coefficient

Pearson correlation coefficient measures the linear relationship between interval data (continuous) (Akoglu, 2018; Chok, 2010; Jaskowiak et al., 2010). It is commonly denoted by the Greek letter ρ (rho). Assume that we are calculating Pearson rho for variables and b. Pearson rho coefficient is calculated as shown in equation 1. The sample covariance and standard deviation are calculated as shown in the equation where ā and $\bar{b}$ are the mean of the variables at hand (Jaskowiak, 2017). Pearson is not applicable when dealing with non-normalized distributions (Akoglu, 2018). Whereas spearman's and Kendal tau comes into place.

$$\rho(a,b) = \frac{\sum_{i=1}^{n}(a_i-\bar{a})(b_i-\bar{b})}{\sqrt{\sum_{i=1}^{n}(a_i-\bar{a})^2}\sqrt{\sum_{i=1}^{n}(b_i-\bar{b})^2}} \qquad (1)$$

Spearman Correlation Coefficient

Spearman correlation coefficient is considered an extension for Pearson that deals with ranked ordinal data as well as continuous data and denoted as ρ_s. It measures the monotonic relationship between the variables whether linear or not. It is the most used test for dealing with ordinal ranked data (Chok, 2010; Prematunga, 2012). Spearman's rho is calculated as shown in equation 2 between the assumed variables a and b. For example, let us assume that we have variable "a" which is equal to (23,7,10,15) then the rank of a is (4,1,2,3). The mean of will be calculated based on the obtained rank of the variables. Also, it should be noted that spearman outperforms Pearson in case of outlier's presence in a sample (Jaskowiak et al., 2010).

$$r_s = \frac{\sum_{i=1}^{n}((rank(a_i)-\overline{rank(a)})(rank(b_i)-\overline{rank(b)}))}{\sqrt{\sum_{i=1}^{n}(rank(a_i)-\overline{rank(a)})^2\sum_{i=1}^{n}(rank(b_i)-\overline{rank(b)})^2}} \qquad (2)$$

Kendall Correlation Coefficient

Kendall correlation coefficient, tau, is similar to Spearman's rho in terms of the data type and detects monotonic relationship. Kendall's tau is also applicable to use in terms of ordinal as well as continuous data (Chok; 2010). It is denoted by the Greek letter τ (tau), and it is calculated as shown in equation 3 where n indicates the number of pairs. Kendall's tau quantifies the differences between the number of concordant and discordant pairs. Concordant pairs occur when the same order applies to the two sequences. For example if we have two pairs of ranks (a_i, b_i) and (a_j,b_j); these pairs would be considered concordant of $a_i < a_j$ and $b_i < b_j$ or $a_i > a_j$ and $b_i > b_j$ or $(a_i-b_i)(a_j-b_j)>0$. Such pairs could be considered discordant if $a_i < a_j$ and $b_i > b_j$ or $a_i > a_j$ and $b_i < b_j$ or $(a_i-b_i)(a_j-b_j)<0$ (Jaskowiak, 2017).

$$\tau = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} sgn\,(a_i - a_j)(b_i - b_j)}{n(n-1)} \qquad (3)$$

$$sgn(a_i - a_j) = \begin{cases} 1\ if\ (a_i - a_j) > 0 \\ 0\ if\ (a_i - a_j) = 0 \\ -1\ if\ (a_i - a_j) < 0 \end{cases};\ sgn(b_i - b_j) = \begin{cases} 1\ if\ (b_i - b_j) > 0 \\ 0\ if\ (b_i - b_j) = 0 \\ -1\ if\ (b_i - b_j) < 0 \end{cases}$$

2.7 Predicting Project Performance

One of the major challenges of this research is the type of data that was being collected. In this regard, project performance prediction models using classification methods have been studied. Many researchers have attempted to study and model prediction processes related to the construction industry (Cheung et al., 2006; Diekmann and Girard, 1995; Kim et al., 2009; Mohamed, 2003; Molenaar et al., 2000; Pinto and Slevin, 1997; Russell and Jaselskis, 1992; Sanders and Thomas, 1993).

One statistical method used is multiple regression analysis (Kim et al., 2009), and it is common for modeling prediction models for project performance (Chan et al., 2001; Diekmann and Girard, 1995; Molenaar et al., 2000; Molenaar and Songer, 1998; Russell and Jaselskis, 1992; Sanders and Thomas, 1993). However, a major flaw attributed to this method is that it ignores all the measurement errors attributed to the variables, which often leads to poor prediction quality (Bae, 2005; Molenaar et al., 2000). Since the type of data being analyzed includes ordinal variables, the linearity assumption can not be satisfied in the domain of interest. For interval data type, linear regression comes into play; however, for ordinal data logistic regression is more applicable and has been shown to give better results (Agresti, 2002). In other words, one decides whether to use linear regression or logistic regression depending on the type of dependant variables.

On the other hand, researchers have attempted to predict the performance of projects using artificial neural networks (ANNs). A study conducted by Ling and Lui (2004) identified 11 performance metrics where data was collected using a questionnaire for 33 projects. Based on this, they used correlation analysis to identify the variables that were associated with the identified metrices and eventually used ANN technique to build the prediction model. In this study the authors were able to predict project intensity; construction and delivery speeds; and turnover, system, and equipment quality with a reasonable accuracy (Ling and Lui, 2004). In 2017, a similar study was conducted by Reenu et al. In their study, the performance indicators identified were cost performance, schedule performance, quality performance and satisfaction level. ANN was deployed as the prediction model after using correlation analysis to identify the explanatory variable associated to each of the performance indicators (Reenu et al., 2017). Neural networks have been implemented by other authors to predict project performance (Cheung et al., 2006; Kim et al., 2009; Ughu and Kumaraswamy,2004; Williams, 2002). According to the literature, ANNs are superior compared to linear or logistic regression where they outperform the latter (Dreiseitl and Ohno-Machado, 2002; West et al., 1997; Gronholdt and Martensen, 2005).

2.7.1 Ordinal Logistic Regression

A regression model typically studies the association between the independent and dependant variables ((Larasati et al., 2011). The regression model identifies the magnitude and the effect of the independent variables on the dependant variable (Chen and Hughes, 2004). The two common categories of regression are linear and logistic regression models. As mentioned above, logistic regression is more applicable when the variables are ordinal; therefore, ordinal logistic regression will be discussed in this section.

Ordinal logistic regression is a logistic regression extension that contains two integral parameters, the link function and the coefficients used in the model. The purpose of the link function is to describe the effect of the independent variable on the ordinal dependant variable. There are two common types of link functions which are *logit* and *cloglog* links. The logit function is used when the ordinal scale is equally distributed with *K* number of responses levels where it contains *K–1* logits in the same model. The *logit* function is as shown in equation 4.

$$logit\ [\ P(Y_n \leq j)] = \alpha_j + \beta' x_{n1} \qquad (4)$$

for j=1,,k-1, and β indicates the effects of independent variables, x_n denotes the value of independent variables, y_n denote the responses level at the dependent variable of the subject n.

The *cloglog* function is used where the responses are ranked on a higher level, for example including satisfactory and very satisfactory on a Likert scale. The *cloglog* function is as shown in equation 5.

$$\log\{-log[1 - \ P(Y_n \leq j)]\} = \alpha_j + \beta' x_{n1} \dots \dots \dots \ (5)$$

The coefficients used in the model are β which indicate that as the independent variable changes by one unit that would be associated to the change of the probability of the occurrence of the event by a factor of e^{β}. One of the limitations of building a regression model is having a minimum number of independent variables regarding the sample size. A rule of thumb according to Peng et al. 2002 stated that the minimum ratio of independent to the sample size should be 1:10. This method cannot deal with multicollinearity between the independent variables as it presumes proportional odds for ordinal data (Larasti et al.,2011).

2.7.2 Artificial Neural Networks (ANNs)

ANNs are a data mining technique that has gained popularity in the recent years and performs better compared to other traditional statistical techniques (Larasati et. al., 2011). One of the main advantages of using ANNs are their robust learning capabilities and abilities to estimate nonlinear relationships between the variables without assumptions for the input and the output variables (Larasati et. al., 2011). Also, they do not presume any trend in the relationship between the independent and dependant variables (Larasti et al., 2011). Such characterises enables the model to compute and behave in a process similar to the human brain (West et al., 1997)Garver, 2002). ANNs have been used in various research fields such as construction to model cost predictions (Adeli and Wu, 1998; Cheng et al., 2010; Duran et al., 2009; Hegazy and Ayed, 1998; G. H. Kim et al., 2005; Sonmez, 2004, 2011) and the financial industry to detect fraud, bankruptcy, and planning solicitation (Youn and Gu, 2010). Other areas where ANNs were used include the medical industry to evaluate the effectiveness of some medical treatments (Nguyen et al., 2018).

An ANN network consists of input, output, and hidden layers, as shown in Figure 6. The input layer has one or more neurons (nodes) that represent the independent variables. The output layer also consists of nodes that represent the dependant variables. The output layer represents the model outcome classification decisions. The hidden layers connect the output and input layers, where one or more layers can be present (Navlani, 2019). The number of hidden layers is identified by the user as well as the number of nodes in each layer (Behara et al., 2002)Garver, 2002). For example, Figure 6 shows two hidden layers that each have 4 and 3 nodes, respectively. The user would identify the number of hidden layers and nodes of each hidden layer based on a trial and error by the used to achieve the desired accuracy (Larasati et. al., 2011).

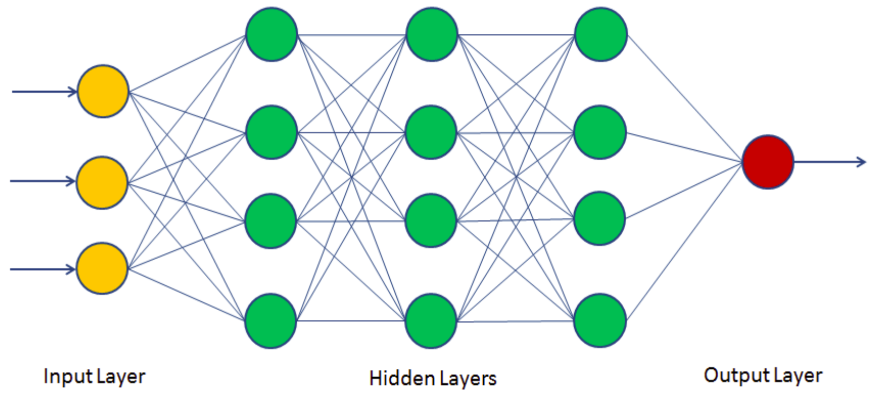

Figure 6. Artificial Neural Network (Navlani, 2019)

The building block in ANN is the neurons located in the hidden layers. For each neuron, the weight *w* is identified through the learning process of the algorithm. Then the weight of each neuron is a result of a summation from each input. Thereafter, the output is identified through applying an activation function to the aggregated weight. The most common activation function is called "Sigmoid function" as shown in equation 6. It acts like the *logit* function in the logistic regression (Larasti, 2011).

$$f(x) = \frac{1}{[1 + \exp(-\eta - x)]} \tag{6}$$

η indicates the threshold (intercept point) and x indicates the aggregate of weighted value.

An important thing to consider when deploying an ANN is the possibility of overfitting the model (Garver, 2002; Deng et al., 2008). An overfitted model occurs when the model is over trained; therefore, the model would memorize the data set and could not be generalized to represent a population. Cross validation could be implemented on the dataset to avoid overfitting. In cross validation, the sample set is divided into *K* number of subsamples where for testing and training (West et al., 1997). Another technique to avoid overfitting is through setting a termination algorithm. One of the commonly used algorithms with supervised ANN is back propagation.

There are three parameters involved with back propagation, which are momentum, learning rate and weight decay (Detienne et al., 2003). Learning rate and momentum are concerned with the percentage error in the iteration, where learning rate is related to the current iteration and the momentum is related to the previous iteration error (Behara et al., 2002). The weight decay parameter works as a decision boundary which usually comes after the cross-validation phase (Dreiseitl and Ohno-Machado, 2002).

2.8 Research Gap

Even though the use of QBS in Canada has been recorded in the literature, this study focused on interviewing a representative sample of large and medium sized cities in Alberta to capture their current procurement practices to select A/E consultant. Despite of the efforts implemented towards adopting QBS, it is still not commonly adopted in Canada. In this regard, the interviewed sample have shared their insights towards adopting QBS in terms of their concerns and benefits. This offered an understanding of the obstacles hindering its wider adoption.

Furthermore, A/E qualifications have been reported in literature while the qualifications commonly adopted by public owners in Alberta remains an unexplored area. Therefore, this study aimed to analyze a sample of RFPs to record the common criteria used to assess consultants by several public owners in Alberta as well as the respective weight of each criteria. Also, the impact of project type on such evaluation criteria was studied.

Researchers have studied various impacts on project performances, as well as structuring prediction models for such purpose. In addition, researchers proposed the A/E qualifications to assess a consultant. However, there is a lack of quantitative evidence that correlating A/E qualifications and their impact on project performances Also the types of A/E consultant's qualifications that impact project outcomes and the magnitude by which they affect performance remains a relatively unexplored aspect in construction literature. Therefore, this research aimed to define, assess, and predict the impact of A/E consultant qualifications, as well as project characteristics, on various project outcomes. In other words, the research aimed to fill in the gap between the decision in selecting an A/E consultant and the impacts such decisions have on project outcomes. Then, the proposed methodology was implemented on a case study of 18 projects in Alberta.

CHAPTER 3. THE CURRENT ENGINEERING PROCUREMENT PRACTICES ADOPTED BY SEVERAL PUBLIC OWNERS IN ALBERTA

3.1 Introduction

Constructions projects have been continuously increasing in complexity, and their success is contingent on numerous factors. Among the most critical factors is the proper selection of a qualified and competent design consultant, which was discussed in the literature review in Chapter 2. In this chapter, current procurement practices of consultant services are studied; 94 requests for proposal (RFPs) were analyzed to identify the common evaluation criteria implemented by public owners in Alberta to assess and award a consultant. The relationship between the project type and the evaluation criteria was also analyzed. In other words, changing the weight (%) assigned to each criterion was studied as the project type changes. Finally, 11 public owners were interviewed to solicit their procurement practices and the interview findings are presented in this chapter. To summarize, this chapter:

1- Analyzes various RFPs to identify the evaluation criteria used to assess consultants adopted by several owners Alberta.
2- Understands the relationship between the evaluation criteria and the project type.
3- Conducts interviews to capture current practices and insights towards adopting qualifications-based selection.

*3.*2 RFP Analysis

94 RFP documents from six public owners in Alberta were analyzed identify evaluation criteria. The owners include 3 big cities, 2 medium cities, and one provincial government in Alberta.

While the evaluation process might differ from one owner to another, this study was only concerned with analysing the common evaluation criteria. The investigated owners divided criteria into mandatory and desirable requirements. Failure by any bidder to fulfill a mandatory requirement led to disqualification (i.e., the offer was not considered). In public projects, selection criteria are altered by the project team according to project characteristics and/or drivers, and the weights of the evaluation categories are assigned by the project team to reflect their relative importance in the evaluation. For confidentiality purposes, the owners' names are not mentioned in the context of the study. The most common evaluation categories across public organizations include experience, human resource requirements, processes, leadership, financial/pricing, previous relationship with the owner, measurement and continuous development, products, models, and deliverables.

The following project characteristics was achieved through analysis of the RFPs dataset: owner, evaluation style, location (city), type of selection, project type, project phase, type of proposal, in addition to the evaluation criteria and the respective weight assigned to each of them. For confidentiality purposes, the owners are referred to as Owner X, Owner Y, etc. The evaluation style was divided into the one-envelope or two-envelope system. In the one-envelope system, the fee and qualification assessment are submitted in one envelope, whereas in two-envelope system they are submitted separately. The main purpose of the two-envelope system is to avoid any bias from revealing the fee proposal at the same time as the technical proposal. The type of selection is divided into open orders, shortlisting after expression of interests, and selection from an existing list of prequalified consultants. The analyzed RFPs included various project types: commercial, roads, industrial, transportation, land development and water/environmental. The project phase characteristic reflects the scope of the consultant and is divided into 1) concept, preliminary, detailed design, tender preparation, and engineering consultancy during construction; 2) preliminary, detailed design and consulting services during construction; 3) planning study; 4) detailed design and project management services during construction; 5) improvement study; and 6) concept and preliminary design. Furthermore, the type of proposal reflects whether the consultant is procured through RFP or negotiated request for proposal (NRFP). In NRFP the owner can negotiate with the highest ranked consultant to reach an agreement; however, in case of disagreement the owner can negotiate with the second best and so on.

3.2.1 Evaluation Criteria

After analyzing the RFPs, evaluation criteria common to several projects were determined and are listed in Table 1.

Table 1: Evaluation criteria as per the dataset

Evaluation Criteria		
Past performance	Safety qualifications	Innovation and value added
Local experience	Financial score	Proposal presentation
Public engagement	Project communication plan	Capacity; resources
Design and technical skills	Project administration and quality	References
Project management interview	Time; schedule; project control	Team composition and experience
Project comprehension and methodology	Firm's experience and qualifications	Proposal quality; completeness. deliverables

As a preliminary analysis of the dataset, the evaluation criteria across different RFPs were counted to get a sense of which criteria are more commonly used to assess consultants' competence. Table 1 shows the criteria that were used to evaluate consultant in different projects and that were repeated in more than five projects. According to Figure 7, three evaluation criteria were found in more than 92% of the dataset: project comprehension and methodology, team composition and qualifications, and financial score. Financial score is also one of the top criteria captured through the interviews where the owners, as discussed in Section 3.3. The next most common criteria are past performance, firm's experience and qualifications, and time/schedule/project control, mentioned in 38% to 45% of the dataset. According to this analysis, it was observed that the team composition and qualifications, as well as the project comprehension, were more important than the firm's experience and past performance. Surprisingly, the financial score was also more important (repeated in more RFPs) than the firm's experience and past performance.

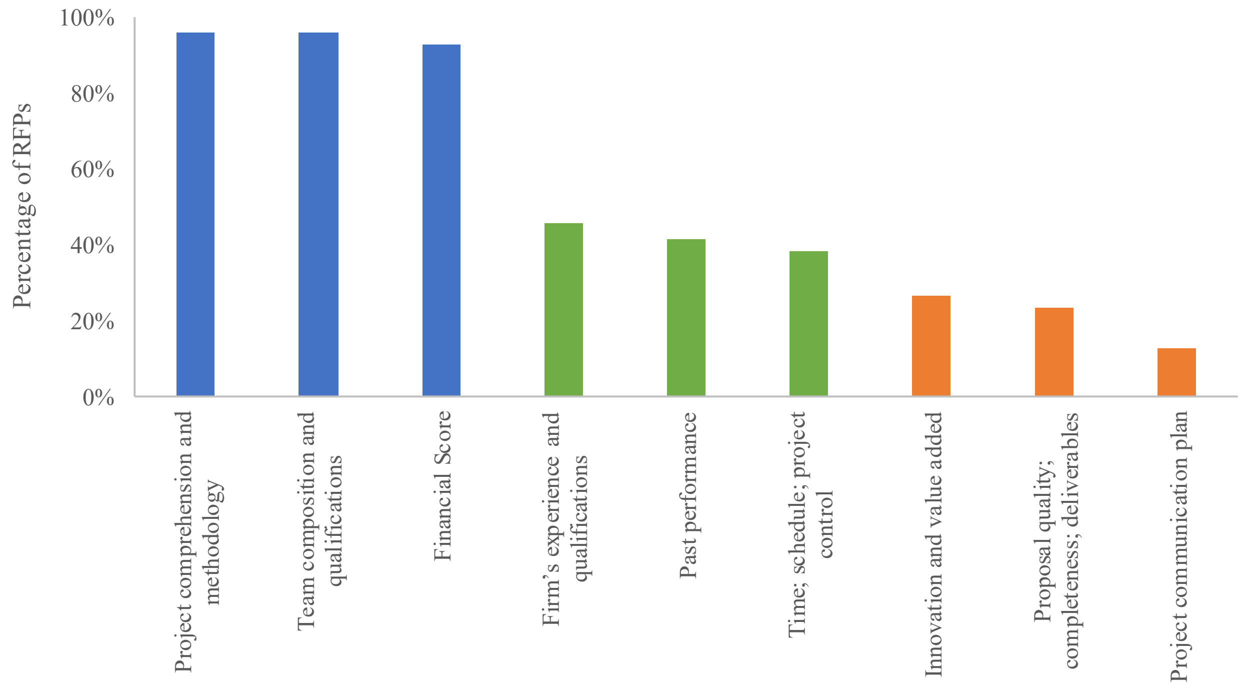

Figure 7. Most used evaluation criteria (on more than 5 projects)

The third most repeated group consists of innovation and value added; proposal quality, completeness, deliverables; and project communication plan which occurred in13% to 27% of the dataset. According to the literature, innovation and value are important for assessing the design consultant; however, it did not match the practices adopted per the dataset, as it was repeated in 27% of the sample.

Figure 8 shows the evaluation criteria that were repeated in five or fewer RFPs – safety qualification, public engagement, capacity/resources, local experience, design and technical skills, project management interview, public engagement, proposal presentation, references, and project administration and quality. Safety qualification, references, and interview were not a significant assessment criterion, which contradicts their importance as determined in the literature review.

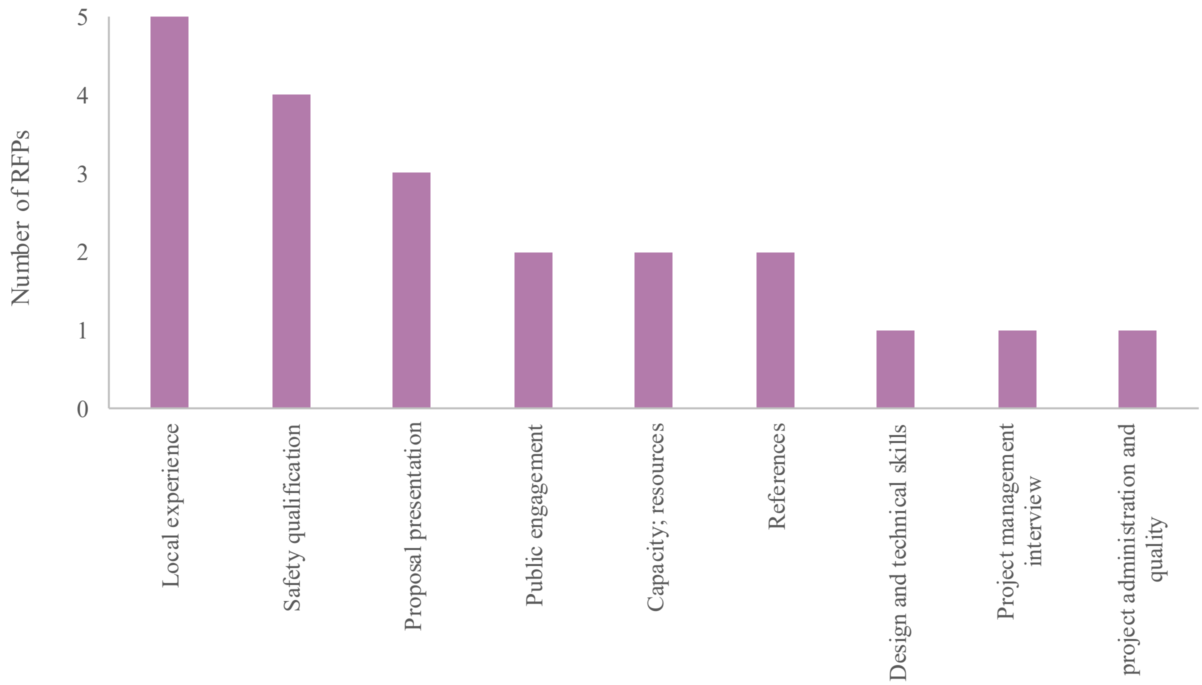

Figure 8. Least used evaluation criteria (on less than 5 projects)

3.2.2 Weights Assigned to Criteria

The weights assigned to each of the evaluation criteria were gathered from the RFP dataset to understand whether there is a trend or a commonality when it comes to evaluating consultants. Furthermore, the aim of such analysis is to investigate the impact of each criterion to select consultant. The importance was reflected as the weight assigned to each criterion, where a higher weight would reflect a higher importance and vise versa. Also, further analysis was undertaken to determine if there is an association among project type, the evaluation criteria, and the assigned weights.

The minimum benchmark for considering an evaluation criterion to be important was set at 25%, resulting in project comprehension and methodology (Figure 9), team composition and experience (Figure 10), financial score (Figure 11), firm's experience and qualifications (Figure 12), past performance (Figure 13), time, schedule and project control (Figure 14), innovation and value added (Figure 15).

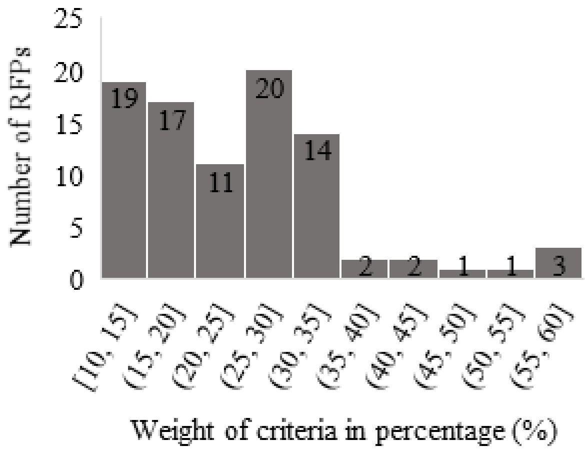

Figure 9. Project Comprehension and Methodology

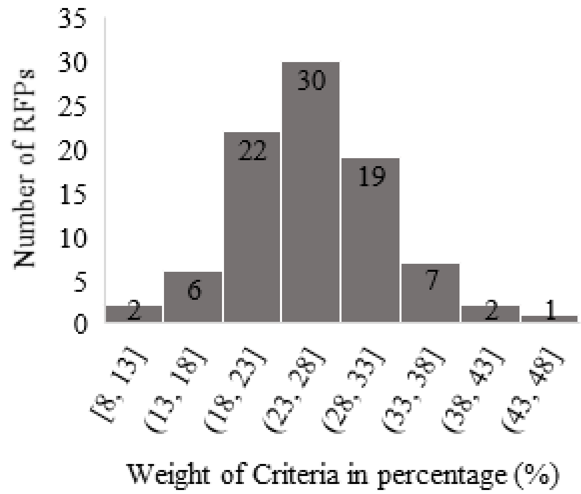

Figure 10. Team Composition and Experience

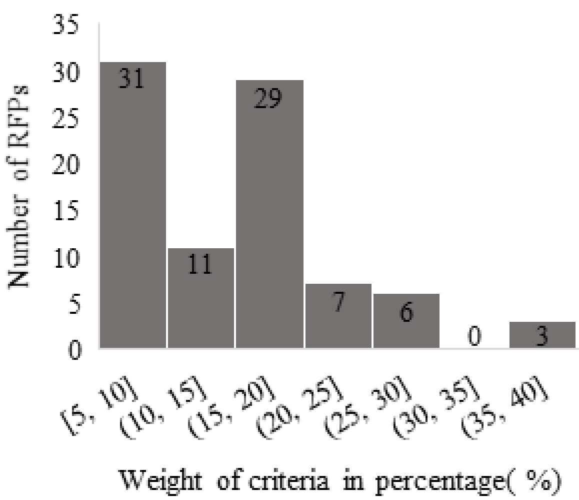

Figure 11. Financial Score

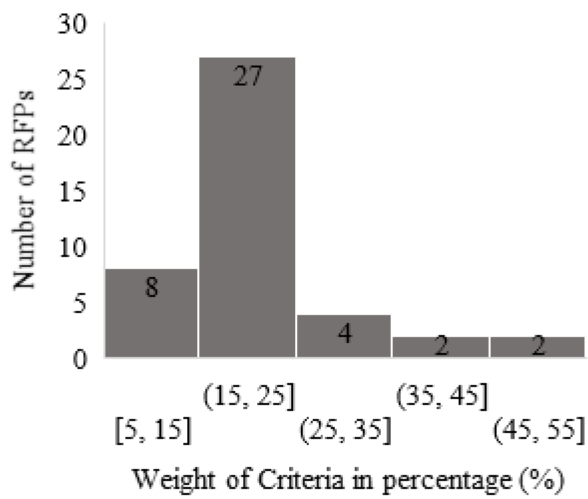

Figure 12. Firm's Experience and Qualifications

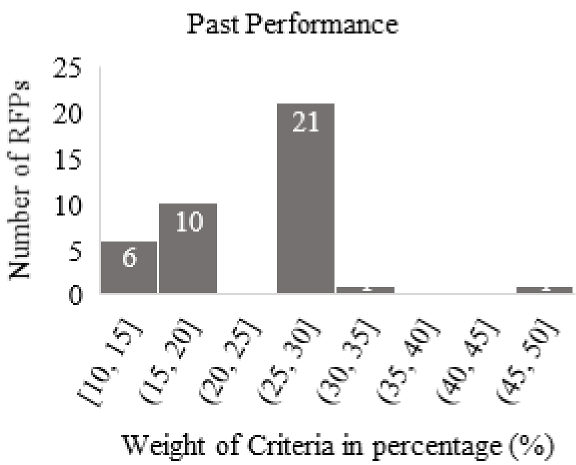

Figure 13. Past Performance

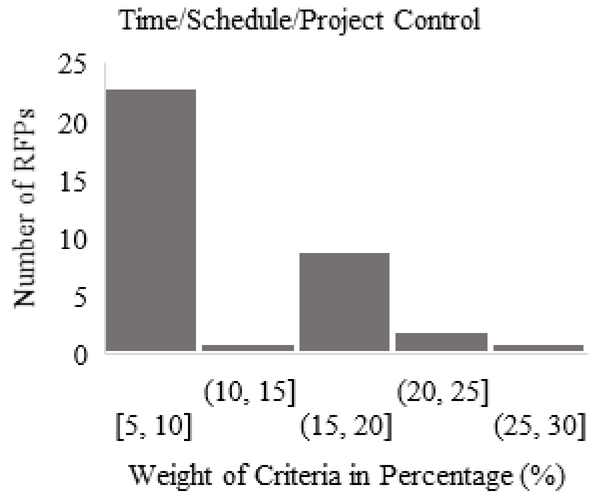

Figure 14. Time/Schedule/Project Control

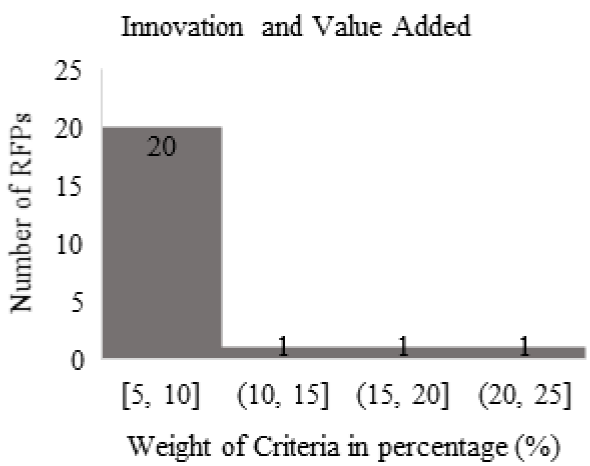

Figure 15. Innovation and Value-Added

The Figures 9–15 show the fluctuations of the weights assigned to the evaluation criteria, which may reflect the lack of standardization of the weights assigned to the criteria. Based on the results shown, the average weights are summarized in Table 3. Project comprehension, team composition, financial score and firm's experience had a similar average weight of approximately 25%. Past performance has an average weight of 18%, and time, schedule, and project control had an average weight of 12%. Innovation and value added comes as the least important criteria with an average weight of 9%. Based on this analysis, it can be observed that financial score is considered more important and has impact in selecting a consultant in comparison to other criteria, which does not reflect the same trends as the literature.

Table 2. Average weight (%) per criterion

Evaluation Criteria	Avg. weight	Minimum Weight	Maximum Weight
Project comprehension and methodology	26%	10%	60%
Team composition and experience	26%	8%	48%
Financial score	25%	5%	40%
Firm's experience and qualifications	25%	5%	55%
Past performance	18%	10%	50%
Time; schedule; project control	12%	5%	30%
Innovation and value added	9%	5%	25%

3.3.3Project Type Impact on Consultant Selection Criteria

Further analysis was conducted to examine whether different project type result in different weights for the criteria, which would indicate a relationship between the two. If no relationship exists, then the projects would follow the generic criteria and weights as summarized in Table 2. The first step is to specify the number of RFP documents according to project type as shown in Table 3. Accordingly, the two prominent project types are roads with 51 corresponding project RFPs and Land Development with 27 corresponding project RFPs.

Table 3. Project type and corresponding number of RFPs

Project type	Roads	Commercial	Transportation	Land development	Water/ environmental	Industrial
Number of RFPs	51	1	6	27	8	1

The frequency of recurring in RFPs of each project type (roads and land development) along with their respective average weights are presented in Tables 4 and 5, respectively. Based on these observations, the most commonly occurring criteria used for road projects are team composition and experience (100%), project comprehension and methodology (98%), financial score (92%), followed by past performance at 53% and time, schedule, project control at 41%. Firm's experience and qualifications, as well as innovation and value added, ranked the lowest at 35% and 22%, respectively. The sequence differs under land development projects with both project comprehension and methodology, as well as financial score, occurring among 93% of the RFPs.

Team composition and experience and firm's experience and qualifications ranked third and fourth with 89% and 63% rates, respectively. Time, schedule, project control; past performance; and innovation and value added ranked the lowest at 33%, 33%, and 26%, respectively. The difference in order and occurrence frequency of criteria between the two types of projects indicates that project type can impact what criteria are used by owners to evaluate A/E firms.

Table 4. Roads Project Evaluation Criteria

Evaluation criteria (Roads)	Occurrence in RFPs	Average weights (%)
Team composition and experience	100%	24%
Project comprehension and methodology	98%	26%
Financial score	92%	17%
Past performance	53%	26%
Time; schedule; project control	41%	9%
Firm's experience and qualifications	35%	19%
Innovation and value added	22%	8%

Table 5. Land Development Projects Evaluation Criteria

Evaluation criteria (Land Development)	Occurrence in RFPs	Average weights (%)
Project comprehension and methodology	93%	28%
Financial score	93%	16%
Team composition and experience	89%	27%
Firm's experience and qualifications	63%	27%
Time; schedule; project control	33%	17%
Past performance	33%	22%
Innovation and value added	26%	9%

Similarly, examining the average assigned weights of each criterion across both project types reveals some differences, although less significant for some criteria. Under Road projects, the three criteria with highest weights of 26%, 26%, and 24% are project comprehension and methodology, past performance, as well as team composition and experience, respectively. On the other hand, the three highest weighted criteria under land development projects are project comprehension and methodology (28%), team composition and experience (27%), and firm's experience and qualifications (27%). Both project types had innovation and value added and financial score weighed low. While time; schedule; project control ranked 9% only under road projects, this criterion weighed almost double at 17% under land development. While firm's experience and qualifications weighed 27% (3rd) for land development projects, this criterion was less important for road projects, weighing only 19%.

These findings reveal that some criteria's weights and repetition percentages among the RFP dataset were significantly affected by project type while some criteria were similarly adopted and weighed across both types of projects.

3.3 Preliminary Interviews

3.3.1 Interview Structure and Participants

The study initially involved 14 participants, and all represented public owners across Alberta from federal, provincial, and municipal entities. In addition to sending survey to the participants, an interview phase was undertaken prior to that, which ensured that all participants would answer questions related to current practices. The main purpose of the interview was to capture their insights regarding current practices and the internal procurement process. Furthermore, structured interviews allow for discussions and document sharing. The interviews were conducted with procurement directors or branch managers.

This stage started by contacting the 14 participants, and which 11 participants agreed to the initial interview. The 11 organizations represent municipalities of major cities and counties, as well as governmental organizations in Alberta. The participants were asked about their commonly used procurement methods for selecting professional A/E services on public projects, after which, the research team observed that the interviewees might not be aware of all the details needed by the research team. Consequently, the research team conducted a second round of meetings with the same and/or other expert(s) of the same organizations. In the later meetings, the interviewed experts were questioned using the same set of questions; however, in most cases the questions were tailored by the results of the initial interview.

3.3.2 Interviews Findings

Once the initial interviews were conducted, it was observed that majority of the participants would divide the procurement strategy according to the service fee. For purpose of this study, the highest service fee category for all participants is included and the other categories are excluded. Most of these organizations usually adopt the lowest-price bid procurement approach for small-scale and standard noncomplex projects. However, the alternatives used differ within and across organizations for large scale projects depending on the nature, scope, and disciplines. Moreover, it should be noted that some of the participants would perform a two-stage procurement process through having a Request for Qualification (RFQ) stage prior to proposals submittal. The purpose of such strategy is to obtain a list of prequalified vendors and service providers' to be used in stage two for the proposal submittals for a certain project. However, some participants who adopted a two-stage process would still perform a one-stage process such as a direct RFP. The project team decides which strategy best suits the project nature and discipline. This is a major issue as it reflects the lack of standard process in organization, and it urges the need for further research.

Based on the study findings, the services procurement practices could be categorized into four practices which are described here. In the best value procurement (BVP) method, the vendors are assessed based on qualifications together with fee proposal. However, some participants would include an interview as part of qualifications assessment to capture hard-to-quantify information such as the team understanding of the project scope. In BVP, the proposal can be submitted by the vendors either in one envelop or two envelopes. The one-envelope system includes the qualification and the fee proposal in one envelop. However, in the two-envelop system the qualification proposal and the fee proposal are submitted separately, and the qualification assessment envelop is opened and ranked first, followed by opening the fee proposal envelop. The purpose of the two-envelop system is to reduce the chances of influence and bias due to the fee proposal. Finally, QBS selects consultants based on their qualifications and experience. In 1972, the Brooks Act (Public Law 92-582) declared QBS as the official procurement method for consultant selection for the US government. The process starts submitting a RFQ, and the firms are short listed based on qualifications and experience. Thereafter, the short-listed firms are interviewed, and the top-ranked firm works with the owner to define the scope and negotiate the price. If an agreement cannot be reached, the owner ends negotiations with the first-ranked firm and starts negotiations with the second-ranked firm. The process focuses on qualifications, competence, previous performance, and experience.

Figure 16 summarizes the number of participants adopting each procurement strategy. As mentioned before, the total number of participants in the study is 11 firms. BVP using one-envelop submission was the most common practice adopted by the participants, with six out of 11 participants (55% of the participants as shown in Figure 16). Furthermore, the same number of firms practiced BVP through two-envelope submission and BVP through one-envelope submission where interview was included in the selection process (which is 18% each as shown in Figure 16). QBS was adopted by a minority since only one participant practices this selection procedure. However, some participants performed a few pilot projects using QBS.

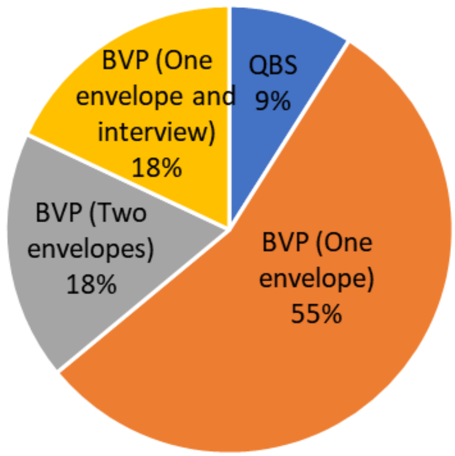

Figure 16. Common procurement methods across Alberta

An important observation is the satisfaction of the participants with their current selection procedure. There was a resistance to change their procurement practice despite many participants mentioning problems associated with their current practice. Such problems may occur because qualifications assessment is relatively qualitative. Therefore, qualifications assessment scores usually balance out, leaving cost as the deciding factor. Public owners face vigorous auditing and public monitoring to avoid corruption and bias in their selection; thus, owners resort to basing their decision on price, which is easily defendable.

One of interview questions was designed to capture the expert's opinion regarding including fee as an evaluation criterion. 91% of the participants believed that fee is crucial to include in evaluating consultants, and only 9% believed that fee is not important in evaluating consultants. Participants were then asked to share their perceptions and experiences regarding the potential benefits and challenges of QBS implementation within their organizations. The findings can be grouped into five categories: a) team structure, b) scope definition, c) nature of QBS, d) long-term benefits, and e) fee competition. These groups are explained in the following sub-sections and summarized in Figure 17.

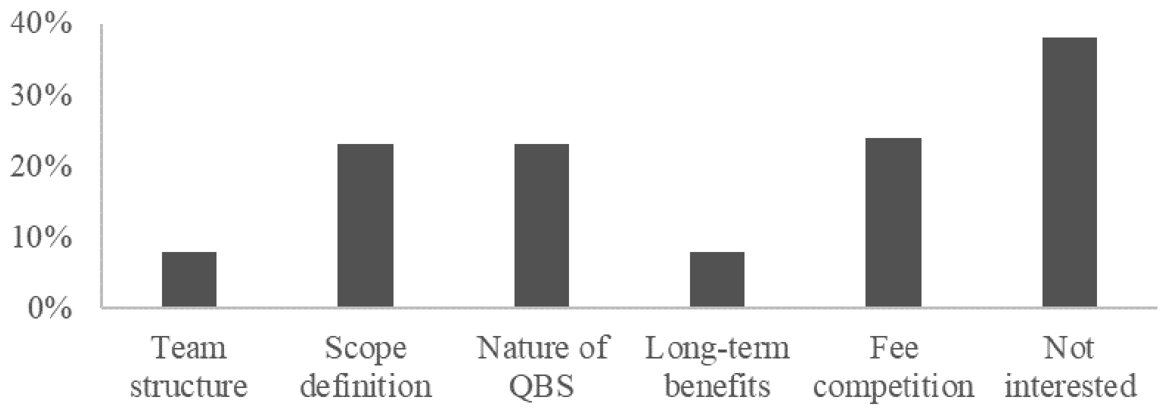

Figure 17. Perceptions of Alberta-based organizations about QBS implementation

(a) Team structure: Owners experience frustrations due to changing team members assigned to a project during the tendering phase. 8% of the owners noted that consultants tend to use the best qualified team members when portraying their qualifications, but once the project is awarded, they choose to replace the assigned personnel. Although this can happen under any procurement approach, it is not common under QBS where the firm's performance is reflected through all its personnel. Additionally, contractual agreements can include specific clauses to avoid team changes from occurring.

(b) Scope definition: Some owners stated that QBS helps to clarify the scope since the firm and the owner sit together and define the scope. Therefore, once the fee negotiations start, there are less likely to be errors in the fee estimation in comparison to other methods. 23% of participants agreed that QBS can provide a clearer scope definition because of joint discussions and scope development between clients and consultants.

(c) Nature of QBS: Some owners believe that the major drawback QBS lies in the qualitative nature in the selection using QBS. As owners face vigorous auditing and public monitoring to avoid corruption and bias, they often resort to basing their decision on price, which can be easily defended. 23% of participants believe that the qualitative nature of evaluating qualifications under QBS is a drawback hindering its wider adoption. Coupled with a lack of studies demonstrating quantitative evidence on the benefits of QBS for project outcomes, owners are often discouraged from adopting QBS on their projects.

Some standardized approaches for scoring and ranking the qualifications of A/E consultants have been developed to resolve the issue of "qualitative" QBS nature.

(d) Long-term benefit: 8% of participants, who have been implementing QBS for years, agreed that QBS provides long-term benefits in the form of better project performance and life cycle cost savings. Such cost savings occur due to the competence of the selected consultant, which eventually leads to fewer errors in design and a lower overall construction cost.

(e) Fee competition: 24% of participants stated that excluding the fee from the proposal would lead to overpricing due to the lack of competition between bidders. Although this is the perception of these participants, QBS can help achieve better value where consultants compete based on qualifications to achieve life cycle performance and cost savings, while negotiating a reasonable fee with the client. This approach avoids overpricing because if a fee is not agreed upon, the second most qualified consultant is selected to negotiate a better fee. Other studies have also indicated that competing based on price can decrease the effort and quality of consultant's performance where A/E firms or contractors tend to reduce their bid price intentionally with the intention to increase fees through scope changes and claims later.

Although most participants shared their overall insights, 38% were generally not interested. It should be noted that the count of the participants is not mutually exclusive; therefore, they add up to 13 instead of 11. The highest percentage of the participants are constituted by the not interested category, followed by scope definition and not easily defendable (23% each). Although most of the participants have shared some of their overall insights, 38% of them were generally not interested in deliberating in-depth regarding the advantages and challenges of implementing QBS.

3.4 Summary

Several RFP documents have been analyzed to understand the evaluation criteria used to assess the consultants adopted by public owners in Alberta. Also, the average weights assigned to these criteria are presented. The evaluation criteria and the assigned weights were studied as the project type changes. The project type roads and land development projects were compared, and there was a relationship among project type, assigned weights, and selection criteria used to assess consultants. In this study, most public owners adopted a one-stage BVP selection process. There is a major fear that QBS may lead to consultant selection based on undefendable and/or biased criteria. Moreover, most of the participants resisted QBS due to the difficulty in defending qualification-based assessment. as it can be subjective and is addressed in the following chapter.

CHAPTER 4. DEFINE, ASSESS, AND PREDICT THE IMPACT OF A/E QUALIFICATIONS AND PROJECT CHARACTERISTICS ON PROJECT OUTCOMES

4.1 Introduction

Performance of design consultant has been shown to impact the cost and quality of facilities (Sporrong, 2011). In 1972, the Brooks Act (Public Law 92-582) declared QBS as the federal procurement process in the US; consequently, it has also been adopted by 46 state governments. Chinowsky and Kingsley (2009) conducted an extensive survey to study the impact of using consultant qualifications on project outcomes in the US. This study showed a correlation between using QBS and traditional project performance evaluation criteria cost, time, and quality. Moreover, the study also found a significant association on qualitative factors, such as societal concerns, trust, and embeddedness.

Chapter 3 described the current practices adopted by several public owners in big and medium sized cities in Alberta as presented in, as well as an RFP analysis to identify the evaluation criteria intrinsic to Alberta and the weight assigned to each evaluation criteria to determine the awarded consultant. The main objective of this chapter is to define, assess, and predict the impact of A/E qualifications and project characteristics on project outcomes.

First, the correlation between A/E consultant qualifications and performance indicators was identified after studying the relationship between A/E consultant qualifications and project performance indicators. To make the model more realistic, the the relationship between project characteristics and project performance was also studied. Integrating project characteristics such as project types, design procurement methods, construction delivery methods, and others allowed for additional understanding of how these variables relates to the project performance and consultant qualifications. A questionnaire was built to capture actual project data from each of the participating public owner. The captured data mainly targeted project characteristics, A/E qualifications, and project outcomes. Furthermore, this chapter presents the development of correlation analysis model to identify the associations between the project outcomes, project characteristics, and consultant qualifications. Also, it presents the analysis of a case study where questionnaire responses were collected.

To summarize, this chapter addresses:

1- Questionnaire design.
2- Development of the correlation analysis model.
3- Consultant qualifications and project characteristics correlated to the project performance based on a case study of 18 projects.

4.2 Questionnaire Procedure and Assumptions

According to Statistics Canada, there are nine steps involved with conducting a questionnaire, which include " formulation of the statement of objectives, selection of a survey frame, determination of the sample design, questionnaire design, data collection, data capture and coding, editing and imputation, estimation, and data analysis" (Statistics Canada, 2003, Chapter 1). A brief explanation for each step and their associated assumptions associated with each is presented below.

4.2.1 Formulation of the Statement of Objectives

Formulation of the statement of objectives is the first step in conducting a questionnaire, and it involves the determination of the necessary information needs, the users and uses of the collected data, the main concepts and the operational definition, the survey content, and the analysis plan (Statistics Canada, 2003). The major purpose of the questionnaire was to find any associations among project characteristics, project outcomes, and consultant qualifications, and the subdivision for each is discussed in Section 4.3. The primary users of the data, public owners in Alberta, were determined by the project initiators (CEA), who also determined the specific list of owners (who are the target population). The reference period of the collected data was projects delivered within the last 10 years. For the analysis plan, the project performance indicators and consultant qualifications were identified according to Sections 2.4 and 2.5. For example, to measure the cost and schedule indices, the actual and budgeted cost and time need to be collected. Therefore, the budgeted and actual cost and time were added as a question in the questionnaire. The required performance indicators and independent variables are as listed in Appendix B.

4.2.2 Selection of Survey Frame

The survey frame identifies the contacting information and means of accessing the target population, as well as the classification of the target population. The contact information and the target population were provided by the CEA and included phone numbers and email addresses of the contact persons. Therefore, the firms were first approached through emails and/or phone calls to describe the study objectives and the required data. Afterwards, meetings were conducted with interested parties to explain the questionnaire design and the nomination of projects. The target population classification is within Alberta as agreed by the project initiators.

4.2.3 Determination of the Sample Design

There are sample survey and census surveys. In a sample survey, the data are collected from a sample of the population; while in census survey, the data are collected from all the parties in the population. There are also probability and non-probability sampling. Probability sampling involves random sampling where each participant has a calculated probability of being selected. However, non-probability sampling uses a subjective method of selection, but it saves time compared with probability sampling. Non-probability sampling assumes that the selected sample is representative of the population. Given the nature of this study, non-probability sampling was the selected approach as the list of participants were predefined by the project initiators.

4.2.4 Questionnaire Design

The questionnaire design involves deciding what questions to ask and how to arrange the questions to obtain the required information. The design of the questionnaire included consulting with the project initiator, reviewing previous questionnaires, and drafting, reviewing, revising, and testing the questionnaire. The project initiators were consulted to make sure that the questionnaire meets the required needs. Thereafter, similar questionnaires were reviewed, such those from Chinowsky and Kingsley (2009) and Ling and Lui (2004). The questionnaire was then drafted. Consulting with the respondents was part of the questionnaire informal testing process. The respondents were provided with a preliminary version of the questionnaire and were asked to share their comments and feedback regarding the potential improvements and modifications of the questionnaire. After capturing these comments, the questionnaire was updated and modified accordingly. The detailed explanation of the questionnaire structure and questions are presented below. It should be noted that a postdoctoral fellow, Dr. Malak Al Hattab, helped in the questionnaire design.

During the conducted interviews in the earlier stage of the study, it was mentioned that there is a lack of a central share central share point where the procurement and project outcomes are compiled. Therefore, the questionnaire was divided into two parts collecting project characteristics, A/E qualifications and project performance indicators as shown in Figure 18. The first part solicited data related to project performance and management related data, and the second part was designed to collect procurement related information.

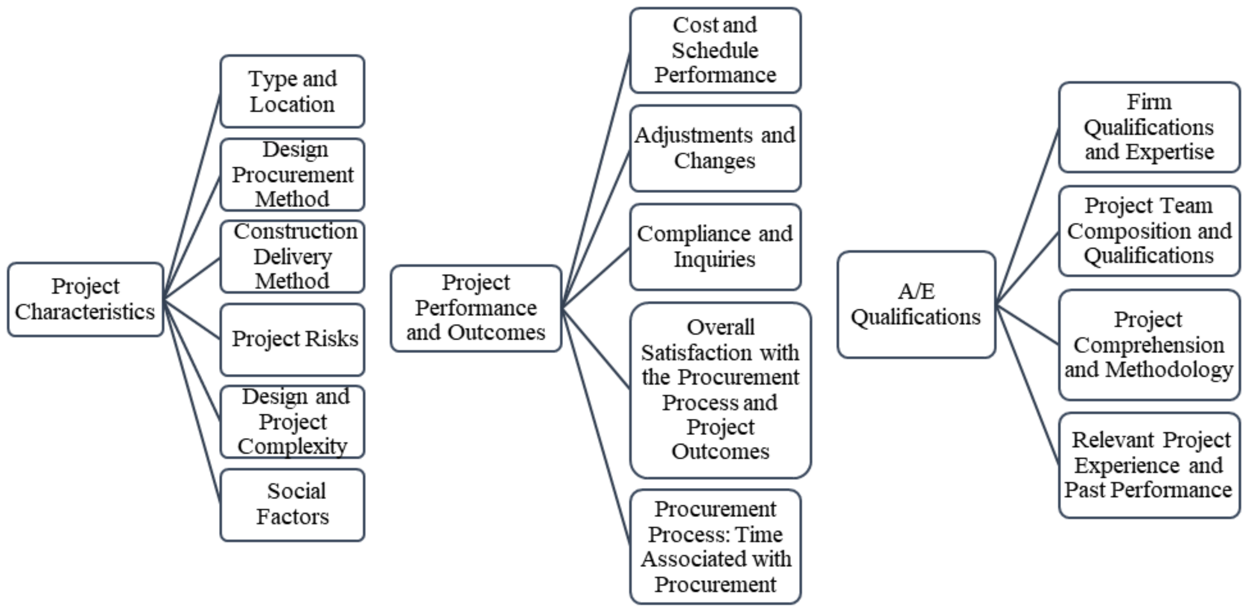

Figure 18. Questionnaire structure

The first part of the questionnaire (Appendix A) captured data related to the overall management performance of the project and project characteristics. It was divided into two sections where the first section solicited data such as project type, location, design procurement method, construction delivery method, and project completion phase, as well as project risks, design complexity, and social factors. The second section captured project performance outcomes, such as cost and schedule, budgeted and actual performances, number of change orders, RFPs, non-conformance reports (NCRs), claims. Furthermore, the impact of change orders and claims on construction schedule (in weeks) and construction cost were solicited, as well as overall satisfaction of the management team with the consultant's performance.

The second part of the questionnaire (Appendix A) is divided into three sections. The first section asks the participants to rate the qualifications of the A/E consultant selected on a given project on scale of 1–5 or not applicable (N/A). This section is further divided into questions that are related to five major evaluation criteria: the firm's experience, project team composition and expertise, project comprehension and methodology, and relevant project experience and prior performance.

The second section is related to the relationship between the owner and the consultant in terms of previous projects, number of years the two parties have worked together, etc. The third section is related to rating the overall satisfaction of the procurement team with the consultant's performance and the procurement process such as the time taken to select a consultant once a bid has been made public.

The questionnaire was structured in reference to the survey developed by Chinowsky and Kingsley (2009). In addition, the evaluation criteria were referenced as per the RFQ and RFP template forms in ACEC-BC's user guide to implementing QBS (ACEC-BC, 2016).

Project Characteristics

The project characteristics were divided into four main categories, which are project attributes, project risks, design and project complexity, and social factors as shown in Figure 19. The project attributes were divided into four elements: project type, design procurement method, consultant firm selection, and the construction delivery method. The design procurement method is also divided into four types: low bid where the consultant with the lowest fee is selected; best value (BV), which combines qualifications and cost; qualification and cost based selection (QCBS), which is like BV where both cost and qualifications are considered in the selection process but higher weight is placed on the qualifications; and QBS where quality is the determining factor, and fee is not a factor in the evaluation process. According to literature, the construction delivery method has been identified as one of the variables that could affect project performance. Therefore, it was included as one of the project attributes in the questionnaire. The respondent can select one of these construction delivery methods: design bid build (DBB), design bid (DB), and construction management (CM), or others.

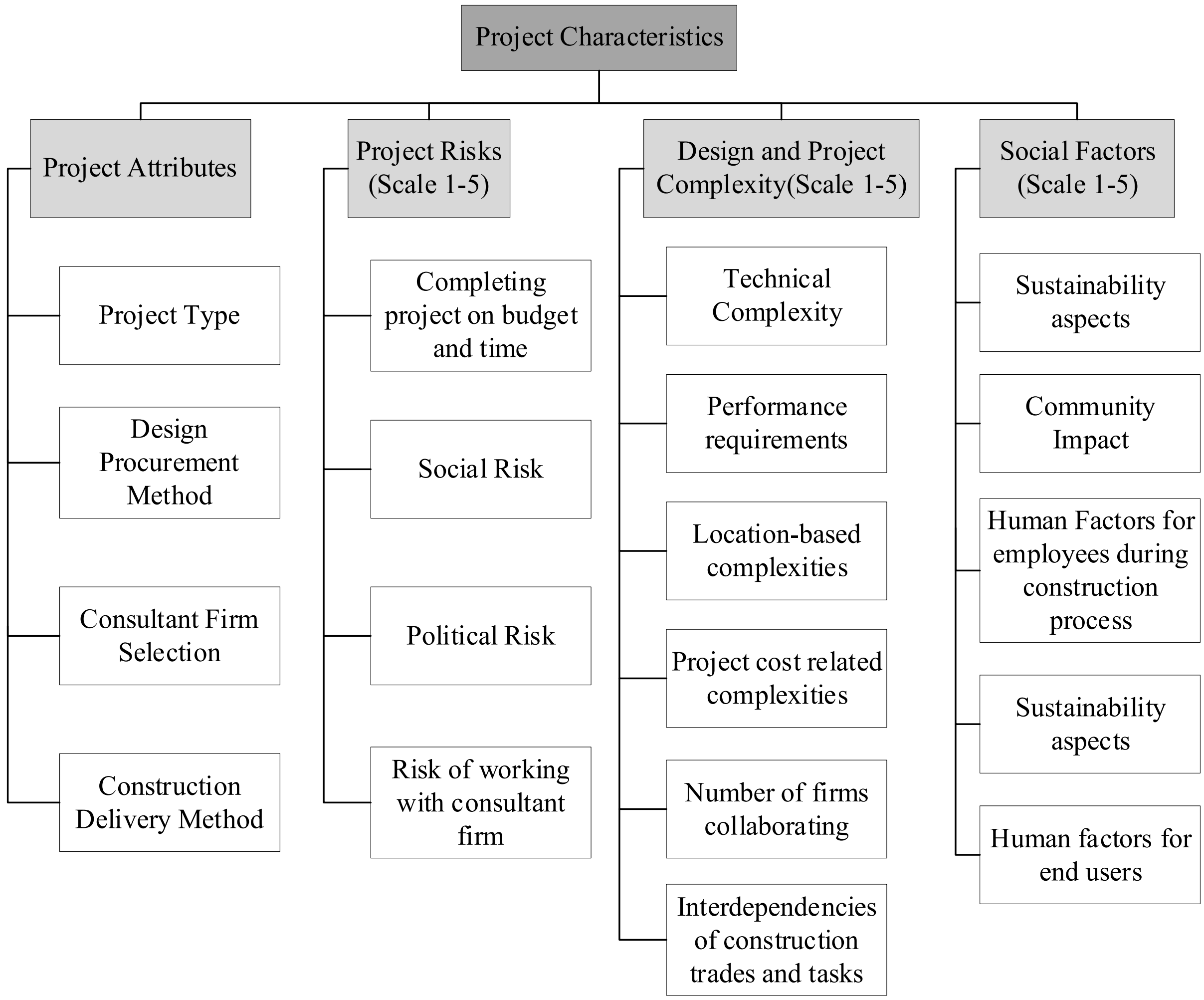

Figure 19. Project characteristics

The project risks include the social risk, such as a community requiring changes to the proposed design; political risk, where political official might require changes to the proposed design; the risk to completing the project on budget and time; and the risk of working with the consultant firms in terms of their qualification, knowledge, or past relationships.

The design and project complexity captures the ranking of six areas on a scale of 1–5. These areas are the technical complexity, which ranks the complexity of technical requirements and the technical specialities required. The second question solicited the complexity of the performance requirements followed by the location-based complexities. Also, the cost related complexity was also ranked by the respondents. One of the major complexities in a project is the degree of the interdependencies of the construction trades and tasks as it impacts the schedule, and a higher degree of dependency would result in a higher risk associated to the execution of the project.

Finally, the number of firms included in the project was also collected, as many firms collaborating in a project would require a strong managerial and communication skills to be able to handle and deliver the project in a successful manner. The questionnaire included a section related to the social factors in which the respondents were asked to rank the extent the consultant addressed the following in their design: sustainability aspects, community impact, human factors for end users and for the employees. The purpose of including this section is to understand the correlation between the social factors and the project performance indicators.

A/E Consultant Qualifications

The qualifications of the consultant are captured in reference to the evaluation criteria outlined in RFP and RFQ templates provided in ACEC-BC's user guide to implementing QBS (ACEC-BC, 2016). This is also inline with the common evaluation criteria based on the RFP analysis as shown in Chapter 3. There are four main categories for the qualifications: firm qualifications and expertise, project team composition and qualifications, project comprehension and methodology, relevant project experience and past performance. This section was filled in by the procurement team assigned to the project where they ranked each of the qualification on a 5-point scale of 1–5 (1 is poor and 5 is excellent). The four categories are further divided as shown in Figure 20.

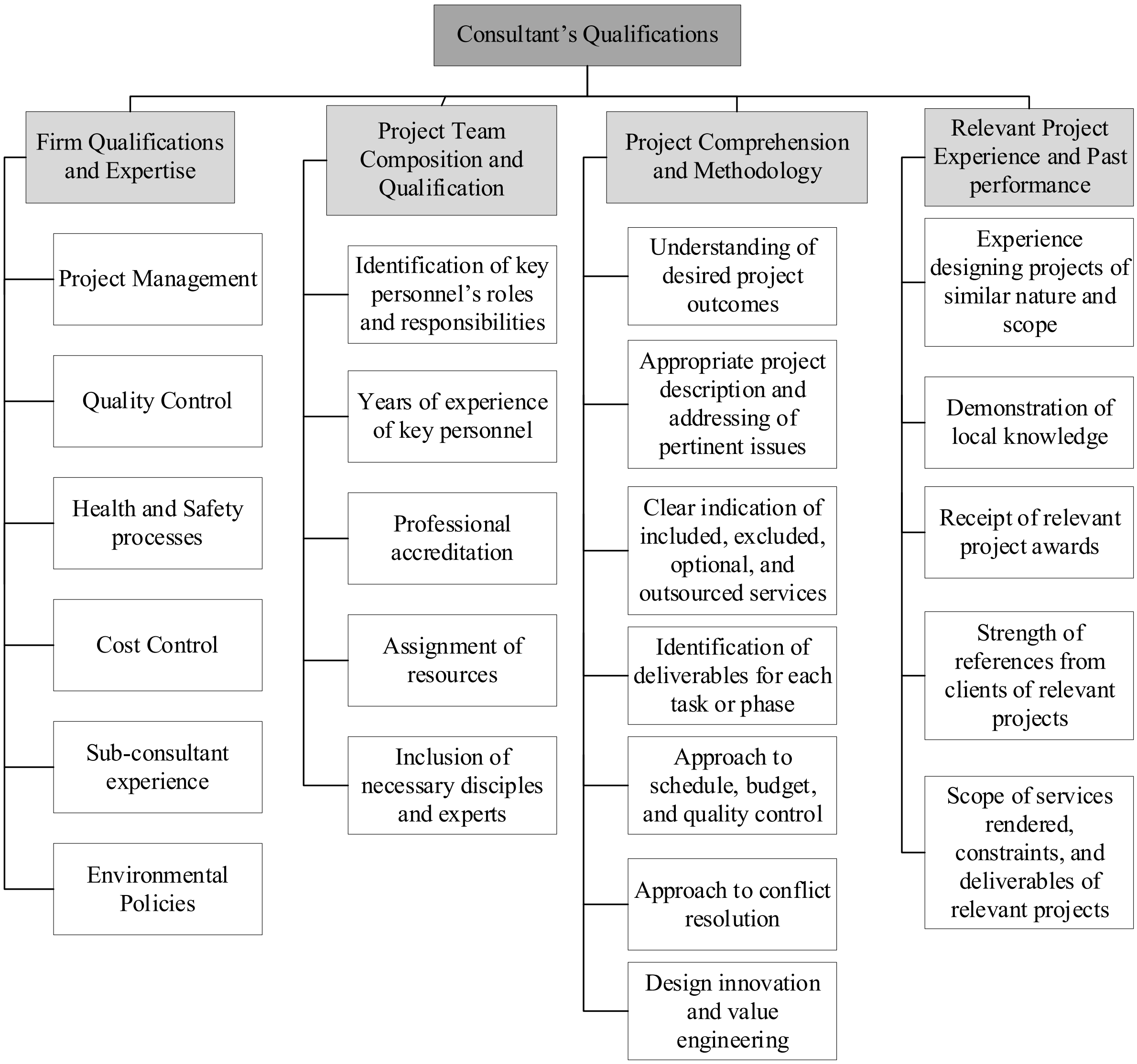

Figure 20. Consultant qualifications

Firm qualifications and expertise were divided into the following areas: project management, quality control, health and safety processes, cost control, sub-consultant experience, and environmental policies. The project team and qualifications targets were ranked in these areas: roles and responsibilities of key personnel, professional accreditation, years of experience of key personnel, assignment of resources, and inclusion of necessary disciplines and experts. The firm's performance in the project and was divided into seven categories: understanding of desired project outcomes, appropriate project description, clear indication of included, excluded, and outsourced services, and identification of deliverables for each task or phase. Conflicts are an inevitable aspect in projects; therefore, the ability of the consultant's conflict resolution strategy was also captured.

The consultant approach to schedule, budget, and quality control is a fundamental element that would affect cost and schedule overruns. Finally, the design innovation and value engineering were ranked.

The fourth section ranked the firm's past performance in five different areas, which are the consultant experience in designing projects of similar nature and scope, as well as the ability of demonstrating local knowledge. The past-experience of delivering projects of similar and relevant scopes was important to assess the consultant's ability and experience. Not only is delivering similar projects important, but also the owners' satisfaction of the consultant performance in such projects is crucial. To cover tis area, the ranking of the strength of the references of these clients was also included. Another point to consider was the scope of services of the delivered relevant projects.

Project Performance and Outcomes

The project performance outcomes were in part A of the questionnaire for the management team. This section contained questions that captured actual project performances (as shown in Figure 21), such as cost and schedule indices as well as changes to project documents. The changes and adjustments to the contract documents consume the project resources; thus, a higher number and cost of such changes is unfavorable in projects. The performance indicators also included compliance and inquiries, time associated with procurement, and owner satisfaction, as discussed below.

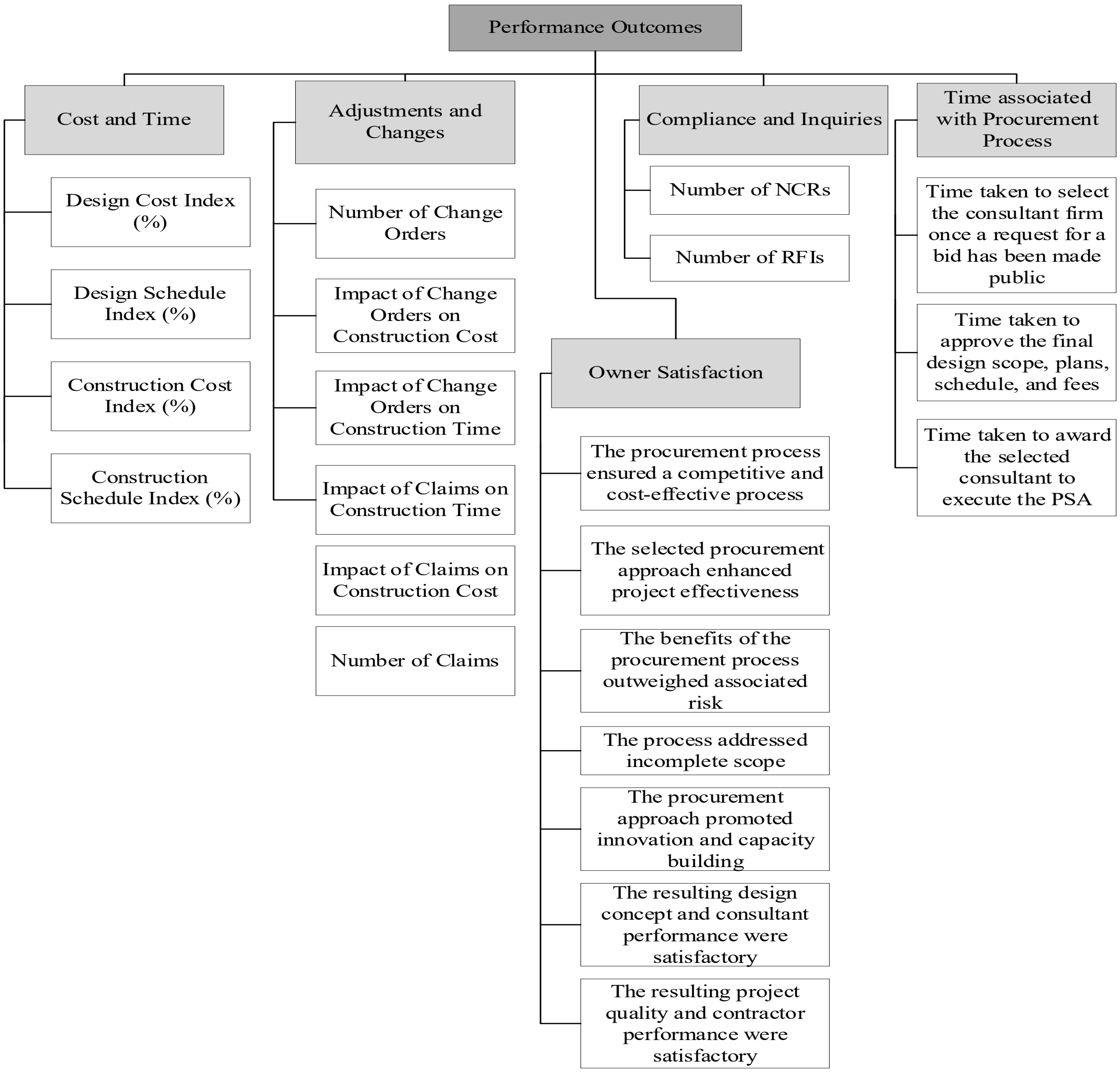

Figure 21. Performance outcomes

Cost and Schedule Indices

To measure the deviations related to the design and construction phases, the cost and schedule indices were calculated for each. The questionnaire was designed to collect the actual and budgeted cost for the design and construction phases, along with the actual and budgeted time for completion in weeks. To measure the deviation of the actual cost and schedule performance in comparison to the budgeted values, indices were calculated using equations X–Y, shown below.

$$Design\ Cost\ Index\ (\%) = \left[\frac{(Actual\ Design\ fee(CAD) - Budgeted\ Design\ Fee(CAD))}{Budgeted\ Design\ fee(CAD)}\right] x100 \quad (7)$$

$$Design\ Schedule\ Index\ (\%) = \left[\frac{(Actual\ Design\ Time\ (weeks) - Budgeted\ Design\ Time(weeks))}{Budgeted\ Design\ Time\ (weeks)}\right] x100 \quad (8)$$

$$Construction\ Cost\ Index\ (\%) = \left[\frac{(Actual\ Construction\ Cost(CAD) - Budgeted\ Construction\ Cost(CAD))}{Budgeted\ Construction\ Cost\ (CAD)}\right] x100 \quad (9)$$

$$Construction\ \ Schedule\ Index\ (\%) = \left[\frac{(Actual\ Construction\ \ Time\ (weeks) - Budgeted\ Cobstruction\ Time(weeks))}{Budgeted\ Construction\ Time\ (weeks)}\right] x100 \quad (10)$$

A low-cost index (approaching zero) indicates less cost overrun, with a negative value reflecting cost savings and vice versa. A schedule index is similar but relates to being ahead of or behind schedule. The design cost index is a percentage that reflects how much the actual design fee deviated from the budgeted fee. Such deviations can be a saving or an overrun; for instance, fee overruns can occur through issuing variations or amendments to the planned design fee. The design schedule index is a value that measures deviations from the planned completion time from the design schedule, which can be being ahead of or behind schedule. The construction cost index is an indication of whether the actual construction cost was below or over the planned budget. The construction schedule index measures the deviations in construction time relative to the planned schedule.

Adjustments and Changes

Changes and adjustments consume project resources and time. The survey quantified the changes and adjustments through soliciting the number of issued change orders and claims, as well as the impact of both on the construction cost and schedule (in CAD and as a 5-point scale from 1–5). Another measure of project performance is related to change orders and claims. The survey was structured to capture data such as the number of claims and change orders. However, numbers themselves are not an enough indication of the impact of change orders and claims on project budget and schedule; therefore, the impact on the construction schedule and cost were collected.

Compliance and Inquiries

The compliance and inquiries were quantified through capturing the number of NCRs and requests for information (RFIs). NCRs are issued to address a deviation from the project specifications from either design or construction. NCRs usually relate to quality issues where the work meet to achieve standards and specs (Rodriguez, 2019). RFIs are usually issued by the contractor to the owner's consultants to inquire about certain subject manners. Many RFIs and NCRs are unfavourable as they consume time and exhaust the project resources.

Time Associated with Procurement

Another measure of project performance is related to the time associated with the procurement process, such as time to select consultant once the bid is made public; the time taken to approve the final design scope, plans, schedule, and fees; and the time taken to award the selected consultant to execute the professional services agreement (PSA). The respondents were asked to answer an open-ended question that indicates the duration in weeks. The time taken to approve the final design scope, plans, schedules, and fees includes the submittal and approval of these documents. The time between selection and awarding was also captured by the questionnaire. The duration includes the time of negotiations and contract signature once the bidder is selected.

Owner Satisfaction

The owner's satisfaction was captured in Part A and Part B of the survey to reflect the satisfaction by both the procurement and the management teams. The respondents were asked to provide their ranking of the owner satisfaction on a scale of 1–5 for seven satisfaction areas. A higher satisfaction from the owner side is a favorable performance outcome. These areas included ranking of the procurement process in terms of cost effectiveness, project quality, innovation, and capacity building; outweighing associated risks; and addressing incomplete scope. The rest covered the satisfaction rankings with the design concept and consultant performance, as well as contractor performance.

4.2.5 Data Collection

Data collection involves the process of gathering the required information and includes four methods: self-enumeration, direct observation, electronic data reporting, and using administrative data. The selected approach was self-enumeration where the questionnaire was completed without the assistance of an interviewer. However, meetings were conducted with designated intermediaries from each firm. The intermediaries were responsible for identifying applicable projects and recruiting participants within the firm to complete the questionnaires. During these meetings, the nomination criteria for the projects were discussed with the intermediaries, and the questionnaire was explained to communicate such information with the nominated participants. It should be noted that Eng. Maria Al-Hussein coordinated and facilitated the data collection process.

Data collection could either be paper-based or computer-assisted. The questionnaire was developed using a computer-assisted method, which facilitates data capture to transform the responses into a computerized format and allows for easy identification and control over invalid responses.

4.2.6 Data Capture and Coding

Data capture and coding was not performed in the computer-assisted questionnaires, as it involves transforming the responses to a computerized format.

4.2.7 Editing and Imputation

Once the data was collected, editing of the collected responses took place. This process involved identifying missing, invalid, and inconsistent entries. Some missing entries were dealt with through follow-up meetings. Once these issues were fixed, the missing entries related to uncompleted projects were then imputed, as thoroughly explained in Section 4.3.1.

4.2.8 Estimation

Estimation is calculated in probabilistic sampling approach to determine the sampling error and generate estimates of the conclusions. However, it is not applicable in this case given that non-probabilistic sampling approach was followed. The reasoning for the selected list of participants is described in Section 1.4.3.

4.2.9 Data Analysis

This stage was performed after the data were collected and edited. It involved the analysis and relating the survey results to the questions mentioned in the statement of objectives. The data analysis methods and conclusions inferred from the responses are described in the rest of this chapter and in Chapter 5.

4.3 Correlation Analysis Model Development

Correlation analysis (CA) was selected, to investigate the statistical significance and magnitude of the relationship between project characteristics, A/E qualifications, and project performance outcomes. Using CA helped to identify which factors affect project performance. Based on the literature, CA is a feature selection method commonly used to improve the learning knowledge performance. For this research, the features were the A/E qualifications and project characteristics (independent variables), and our dependent variables were the project performance outcomes. The explanatory variables were used to predict the dependent variables to validate the accuracy of the output subset.

The inputs to the correlation model were consultant qualifications and project characteristics, and the model found the associations between each and performance indicators, as described in Section 4.2.3. The correlation model then processed the correlation matrix to obtain the list of qualifications that are related to each performance indicator, along with a list of project characteristics that correlate to each performance indicator. This process is illustrated in Figure 22.

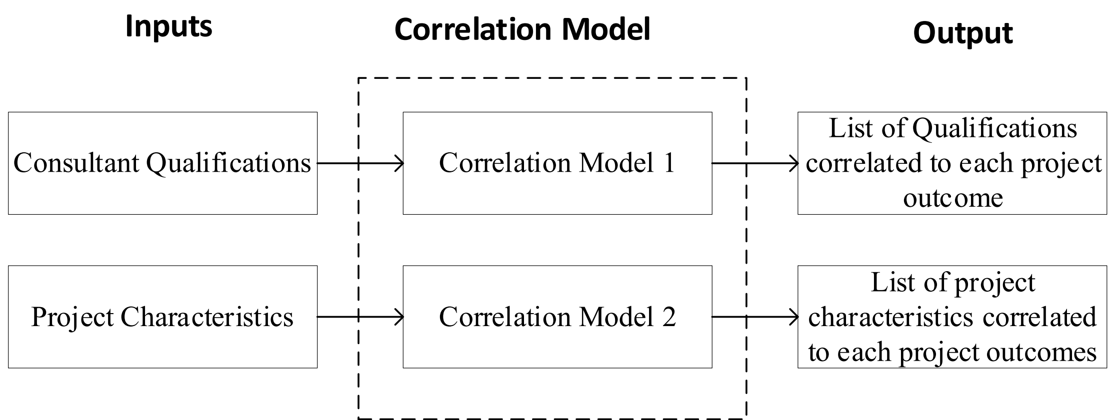

Figure 22. Correlation Model Process

4.3.1 Dealing with Missing Data

Dealing with missing entries from the questionnaire was crucial before proceeding to analysis of the sample set. The construction phase of some of the sampled projects was still in progress, which resulted in some missing data related to project outcomes. Also, there were some sections in the questionnaire that were structured where the respondent can choose from a 5-point evaluation scale or a N/A response. The N/A response in such case was substituted by a zero for the numerical analysis, which made the final scale a 6-point scale. Obtaining project data (submitted questionnaire for part A and part B) was a time-consuming and difficult process given the unprecedented COVID-19 situation. Therefore, samples were kept even they had some missing entries. In such cases, missing entries had to be replaced.

As a result, a method well-suited for data was used to substitute the missing data. According to the literature, a common practice is mean and median substitution; however, mean substitution typically distorts other characteristics of a variable's distribution, giving a biased estimate (Malarvizhi and Thanamani, 2012; Raghunathan, 2004). A weighted moving average is also commonly used but was deemed inapplicable to our dataset since each project is unique (Demirhan and Renwick, 2018; Raghunathan, 2004). K-nearest neighbor (K-NN) imputation was used, where the similar data points are first grouped together, and the missing value for each group is substituted by the mean of the group (Malarvizhi and Thanamani, 2012). It should be noted that using imputations can contribute to errors and that the projects that are still in progress could change the model's performance.

4.3.2 Dealing with Categorical Variables

The survey questions captured data of different scale types; the obtained data are ordinal from a 5-point scale, interval (continuous), and categorical (nominal). To process the categorical variables to obtain a numerical correlation coefficient, these variables were transformed to numerical values. To achieve this, two encoding methods – ordinal coding or one-hot coding (Potdar et al., 2017) – could be implemented for descriptive project characteristics. In one-hot coding, a single variable with *n* observations and *d* number of distinct values is transformed to *d* number of variables where each includes *n* number of values. For each variable, (1) indicates the presence of this variable and (0) its absence. This method is one of the most widely used encoding techniques. However, it results in many variables. On the other hand, in ordinal coding, each distinct value in a variable is replaced by an integer. Unlike the one-hot coding it does not add any new columns to the data. However, it assumes a non-existent order to the values (Eye et. al., 1996). To avoid the large number of variables associated with one-hot coding, ordinal coding was selected. The numerical integers used for the categorical variables, which are project attributes, are shown in Table 6.

Table 6. Categorical Variables

Project Attributes	Description
Project Type	1= Transportation, 2= Institutional,3=Residential,4=Water/Environmental,5 =Neighbourhood Rehabilitation,5= Housing and Commercial
Design Procurement Method	1= Non-QBS,2= QBS
Consultant Firm Selection	1= Prequalified list, 2= Open Bid, 3= Competition
Construction Delivery Method	1= CM, 2= DBB, 3= DB, 4=PM

4.3.3 Correlation Coefficients

The survey questions captured data of different scale types; the obtained data are ordinal from a 5-point scale, interval (continuous), and categorical (nominal). The ordinal data are the ranking of the A/E qualifications, project risks, design and project complexity, social factors, impacts of claims and change orders, overall satisfaction of the management team with the consultant's performance, the overall satisfaction of the procurement team with the consultant's performance, and the interactions between the consultant and the owner. The interval data are the project performance outcomes, such as planned and actual cost and duration for design and construction phases; impacts of claims and change orders; number of RFIs, claims, NCRs, and change orders; the relationship between the owner and the consultant; and the time associated with the procurement process. The categorical data are some project characteristics, which are project type, design procurement method, consultant firm selection (open bid or prequalified), and the construction delivery method.

In this research, we tried to find correlations between project performance outcomes, which are continuous or ordinal data, and project characteristics (nominal) and qualifications (ordinal). According to the literature described in Chapter 2, there are three commonly used correlation coefficients, which are Pearson, Spearman, and Kendall. Similar studies conducted by Ling and Lui (2004) and Reenu, et al. (2017) used Spearman coefficient to find correlations between nominal, continuous, and ordinal data captured by the survey. Other researchers suggested using Kendal over Spearman as its distribution approaches normality faster (Colwell and Gillett, 1982). Furthermore, some authors suggested that Kendall's tau results in a higher accuracy in comparison to Spearman's (Akoglu, 2018). Considering this, Spearman and Kendall were performed, and their results compared.

The interpretation of the significance of correlation coefficient values varies according to the domain of the research. For example, in psychology, a moderate correlation significance is reported as for values above ±0.4. This value is ±0.3 in politics and ±0.6 in medical research (Akoglu, 2018). According to the construction literature, the reported significant correlations was for values at or above ±0.3. Therefore, the selected benchmark is above ±0.3.

4.3.4 Correlation Between Project Performance and A/E Qualifications (Model 1)

There are seven project performance indicators captured by the survey. The performance indicators are the cost, time, adjustments and changes to contract documents, compliance and inquiries, time associated with the procurement process, and owner's satisfaction. Furthermore, consultant qualifications are captured regarding the evaluation criteria outlined in RFP and RFQ templates provided in ACEC-BC's user guide to implementing QBS (ACEC-BC, 2016). There are four main categories for the qualifications, which are firm qualifications and expertise, project team composition and qualifications, project comprehension and methodology, relevant project experience, and past performance. As discussed before, Kendall's tau and Spearman correlation coefficients were calculated for the variables due to their capabilities in dealing with ordinal and continuous variables. The process is illustrated as shown in Figure 23.

Input	→	Process	→	Output
(see below)		Correlation Analysis (kendall and spearman correlation coefficient)		Correlation Matrix (Correlation coefficients between Consultant Qualifications and Performance Indicators)

Input

Consultant Qualifications

A. **Firm Qualifications and Expertise** :
Project Management
Quality Control
Health and Safety processes
Cost Control
Sub-consultant experience and working relationships
Environmental Policies

B. **Project Team Composition and Qualifications :**
Identification of key personnel's roles and responsibilities
Years of experience of key personnel
Professional accreditation
Assignment of resources
Inclusion of necessary disciples and experts

C. **Project Comprehension and Methodology**
Understanding of desired project outcomes
Appropriate project description and addressing of pertinent issues
Clear indication of included, excluded, optional, and outsourced services
Identification of deliverables for each task or phase
Approach to schedule, budget, and quality control
Approach to conflict resolution
Design innovation and value engineering

D. **Relevant Project Experience and Past performance**
Experience designing projects of similar nature and scope
Demonstration of local knowledge
Receipt of relevant project awards
Strength of references from clients of relevant projects
Scope of services rendered, constraints, and deliverables of relevant projects

Performance Indicators:

A. Cost:
Design Cost Index
Construction Cost Index

B. Time:
Design Schedule Index
Construction Schedule Index

C. Adjustments and changes:
Number of change orders
Impact of change orders on construction cost
Impact of claims on construction cost
Number of claims
Impact of change orders on construction time
Impact of claims on construction time

D. Compliance and Inquiries
Number of NCRs
Number of RFIs

E. Time associated with Procurement Process
Time taken to select the consultant firm once a request for a bid has been made public
Time taken to approve the final design scope, plans, schedule, and fees
Time taken to award the selected consultant to execute the PSA

F. Owner Satisfaction:
Procurement process ensured cost-effective process
The selected procurement approach enhanced project effectiveness
The benefits of the procurement process outweighed associated risk
The process addressed incomplete scope
The procurement approach promoted innovation
The resulting design concept and consultant performance were satisfactory
The resulting project quality and contractor performance were satisfactory

Figure 23. Process for correlation Model 1

Model Input

The inputs to the correlation model are the consultant qualifications and project performance indicators, as shown in Figure 23. The consultant qualifications are ranked on a 5-point ordinal scale. The qualifications cover four different areas, as described in Section 4.2.2. The qualifications were processed after dealing with the missing data through K-NN imputation, as explained in Section 4.3.1. There are seven areas of project performance indicators captured by the survey: the cost, time, adjustments and changes to contract documents, compliance and inquiries, time associated with the procurement process, and owner's satisfaction. Furthermore, the project performance indicators include 22 variables that were also input to the correlation model, as described in Section 4.2.3. The description and scale of the input variables to the correlation model are as shown in Appendix B. The performance indicators include continuous and ordinal variables. The continuous data are the design schedule index, design cost index, construction cost index, construction schedule index, number of change orders, number of claims, number of RFIs, number of NCRs, time taken to select the consultant once the bid has been made public (weeks), time taken to select approve the designs (weeks), and time taken to select the consultant once the bid has been made public (weeks). The impact of change orders and claims were solicited as a continuous number, as well as an ordinal scale from 1–5. These variables include the impacts of change orders on construction cost and time, as well as the impact of claims on construction cost and time. The ordinal variables include the owner satisfaction ranking of seven areas: the ranking of the procurement process in terms of cost effectiveness, project quality, innovation, capacity building, outweighing associated risks, and addressing incomplete scope. Furthermore, the rest covered the satisfaction rank with the design concept and consultant performance, as well as the contractor's performance.

Process

The processing of the inputs was undertaken using *R-Studio* software (Version1.2.5033, RStudio Team, 2020) and the programming language used was *R*. *R-Studio* was selected due to its robust capability and its common use in research. The CAs used in this study were Spearman rank correlation coefficient and Kendall rho, which were implemented in *R-Studio* with correlation package. The source code is shown in Appendix C.

Model Output

The output after implementing the correlation analysis is a correlation matrix that includes the correlation coefficients between the consultant qualifications and performance indicators using spearman and Kendall. Considering the Singapore study and the similarity of the investigated data and outcomes; spearman was selected. Like the literature, the significant correlations were for values equal to or higher than ± 0.3. Based on the correlation coefficients the qualifications that contributes to each of the earlier identified performance indicator are to be extracted and listed.

4.3.5 Correlation Between Project Characteristics and A/E Qualifications (Model 2)

In the previous section, the list of consultant qualifications that were correlated to each performance indicator were identified. However, the project characteristics and associated risks are inherent to each project and would contribute to project performance. In other words, consultant qualifications are not the sole variables in a project; other variables that are related to the project nature ands associated characteristics would also influence the project performance. These include project type, construction delivery method, design procurement method, consultant firm selection (open bid or prequalified), as well as project risks, social impact, and project complexities, which will be referred to as “project characteristics”. It is crucial to understand the correlation between these variables and the earlier proposed project performance indicators. In this regard, a correlation model was developed to identify the list of project characteristics that are correlated to each performance indicator. The process is illustrated as shown in Figure 24.

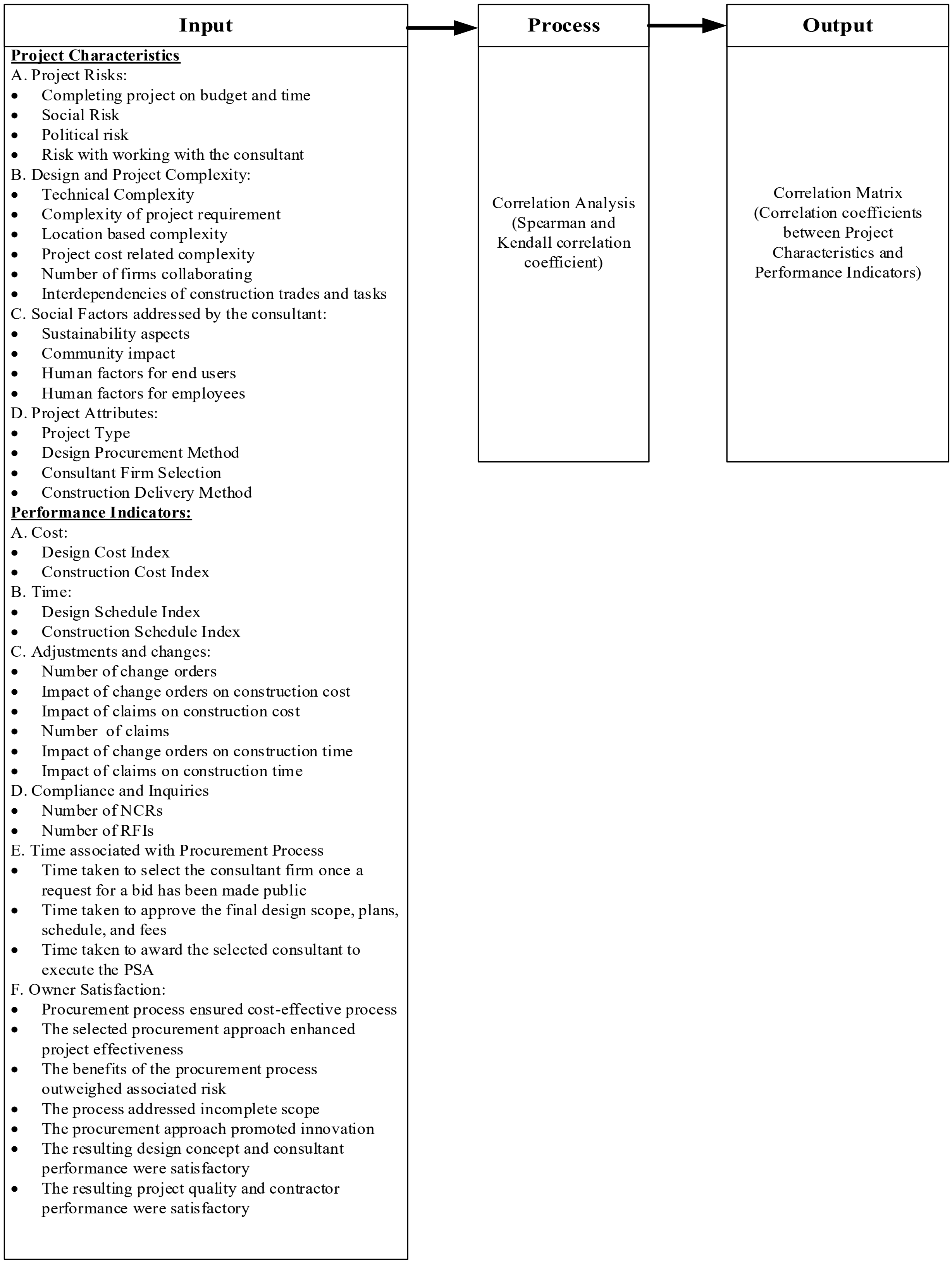

Figure 24. Process for correlation Model 2

Model Input

The model inputs were obtained through the survey that was explained in Section 4.2, which included the project characteristics and performance indicators shown in Figure 24. The model inputs include data of different scale types: categorical (nominal), ordinal of 5-point scale, and interval (continuous). The categorical data are the project type, design procurement method, consultant firm selection (open bid or prequalified), and the construction delivery method. The ordinal data are the associated project risks, design and project complexity, social factors, and owner satisfaction. The interval data are the project performance outcomes, such as planned and actual cost and duration for design and construction phases; impacts of claims and change orders; number of RFIs, claims, NCRs, and change orders; the relationship between the owner and the consultant; and the time associated with the procurement process. The project characteristics are divided into project attributes, project risks, design and project complexity, and social factors, as shown in Appendix B.

The project attributes were divided into four elements: project type, design procurement method, consultant firm selection, and the construction delivery method. The project risks included the social risk, such as community requiring changes to the proposed design; political risk where political official might require changes to the proposed design; the risk of completing the project on budget and time; and the risk of working with the consultant firms in terms of their qualification, knowledge, or past relationships.

The design and project complexity captures the ranking on a scale of 1–5 in six areas. These areas are the technical complexity, which ranks the complexity of technical requirements and the technical specialities required. The second risk solicited the complexity of the performance requirements followed by the location-based complexities. Also, cost-related complexity was ranked by the respondents, along with the interdependencies of construction trades and tasks. The number of firms in the project was also included. The social factors section included sustainability aspects, community impact, and human factors for end users and for the employees.

Process

As with the first correlation model, the processing of the inputs was undertaken using *R-Studio* software (Version1.2.5033, RStudio Team, 2020) and the programming language *R*. *R-Studio* was selected due to its robust capability and its common use in research. The CAs used in this study were Spearman rank correlation coefficient and Kendall rho, which were implemented in *R-Studio* with correlation package. The source code is shown in Appendix C.

Model Output

The output after implementing the correlation analysis is a correlation matrix that includes the correlation coefficients between the project characteristics and performance indicators. Based on the correlation coefficients the characteristics that contribute to each of the earlier identified performance indicators were to be extracted for coefficients ±0.3.

4.4 Case study

This section covers the analysis of a case study where questionnaire responses were collected and analyzed. The results based on implementing the correlation analysis is also presented.

4.4.1 Questionnaire participants

11 participants agreed to participate in the preliminary interviews to collect general information related to the procurement methods adopted by public owners in Alberta and to capture their insights towards adopting price-based approaches. The subsequent stage aimed for the participants to answer questionnaires to gather additional data about their assessment of A/E consultants on specific projects, as well as project characteristics and performance outcomes. Seven organizations have initially agreed to take part in the surveys, however, due to the unprecedented situation of COVID-19, the number of participants decreased to three, which are the two major cities in the province and one small municipality. The results shown in this section do not reflect the population trend due to its limited size and diversity. However, the conducted models are ready for more data once they are available.

4.4.2 Project Demographics

The project characteristics solicited in part A were the design procurement method, construction delivery method, consultant firm selection, and completion status. The majority of the sample were projects where QBS and QCBS were the A/E consultant procurement methods (seven each), as shown in Figure 25. Only one project was low bid, and the rest are BV (three projects). The sample was further divided into two clusters: QBS and non-QBS. The non-QBS cluster includes any project where the price was one of the evaluation criteria used to assess the consultant. Construction delivery method is one of the captured project characteristics, three responses were captured, which are DBB, DB, or CM. DBB is the traditional delivery method (Shrestha et al., 2007), and most of the sample projects were DBB projects (eleven projects); five projects used CM; and two used DB, as shown in Figure 26.

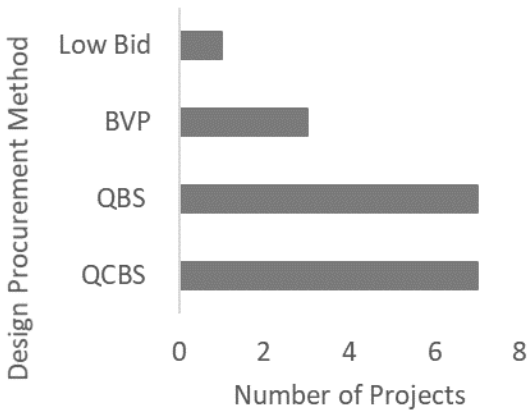

Figure 25. Design procurement method

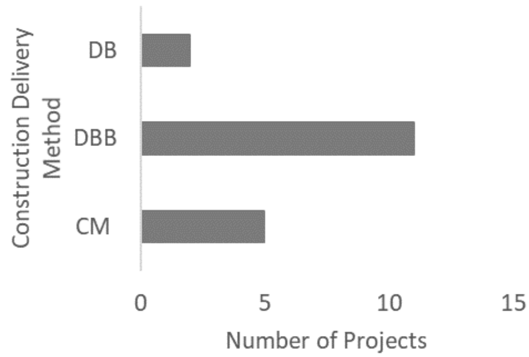

Figure 26. Construction delivery method

The consultant firm selection identified whether the consultant was selected through an open bid or from a prequalified list of consultants. In an open bid, the tender for a certain project is open to for consultants to submit their bids; however, in the latter, the consultants are only eligible to submit their bids if they are on the prequalified list of firms. Prequalification is a process where interested consultants are assessed based on general criteria for a certain type of project and not for a specific project. In Alberta, the prequalification process for public owners assesses consultants based on the type of project, such as functional planning, highways and bridges, water management, quality assurance, or geotechnical and environmental services. The evaluation criteria include corporate information; staff, including their qualifications and team structure; five most recent projects undertaken; and financial information, including the total professional fees for similar projects over the last 1, 3 or 5 years and mandatory certifications such as safety (Statement of Qualifications, 2018). The sample showed equal portions of open bid projects or those where consultants were selected from a prequalified list (nine projects), as shown in Figure 27.

The completion status was either design and construction are complete, or the design is completed, and construction is still in progress. As shown in Figure 28, five out of 18 projects were still in progress, and the rest were complete.

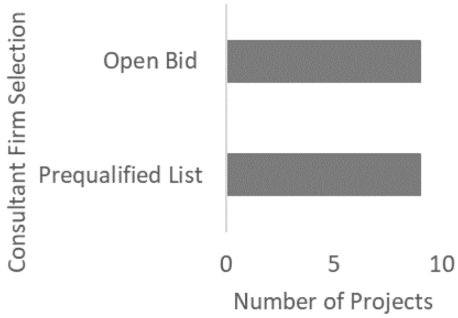

Figure 27. Consultant firm selection

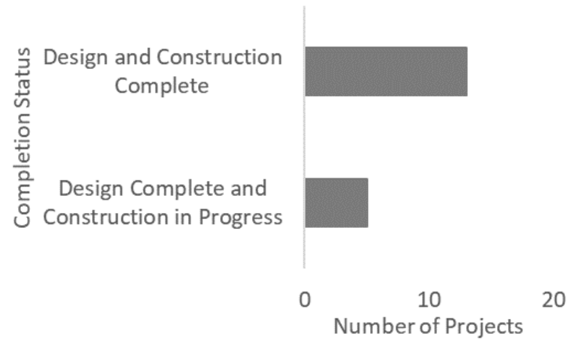

Figure 28. Completion status

4.4.3 QBS vs. Price-Based Approaches Project Demographics

To assess the impact of including the price as an evaluation criterion, the projects were grouped into two clusters based on the design procurement method characteristic. The first group – Group A – included projects where QBS was the procurement method (not including price as an evaluation criteria). The second – Group B – was comprised of procurement methods where price is included as an evaluation criterion: are QCBS, BV, and low bid.

General project demographics for project characteristics were performed based on such grouping, as shown in Figure 29. For project type, both groups contained water/environmental (29% of Group A and 27% of Group B), institutional (29% of Group A and 27% of Group B), and transportation (43% of Group A and 18% of Group B). The remaining project types only belonged to Group B: infrastructure projects (9%) and residential (18%) of Group B. The bidders for most of Group A were selected from a prequalified projects list of consultants (86%), with the remaining selected through open bid, whereas most of Group B was selected from open bid. DBB is the construction delivery method adopted by majority of Group A and Group B projects (71% and 55%, respectively). None of Group A projects were delivered through a CM approach, while it comprised 45% of Group B. Most of the projects grouped under A and B were completed, and they also shared a similar percentage of projects where the design was completed but the construction is either in progress or did not start (29% and 27%, respectively).

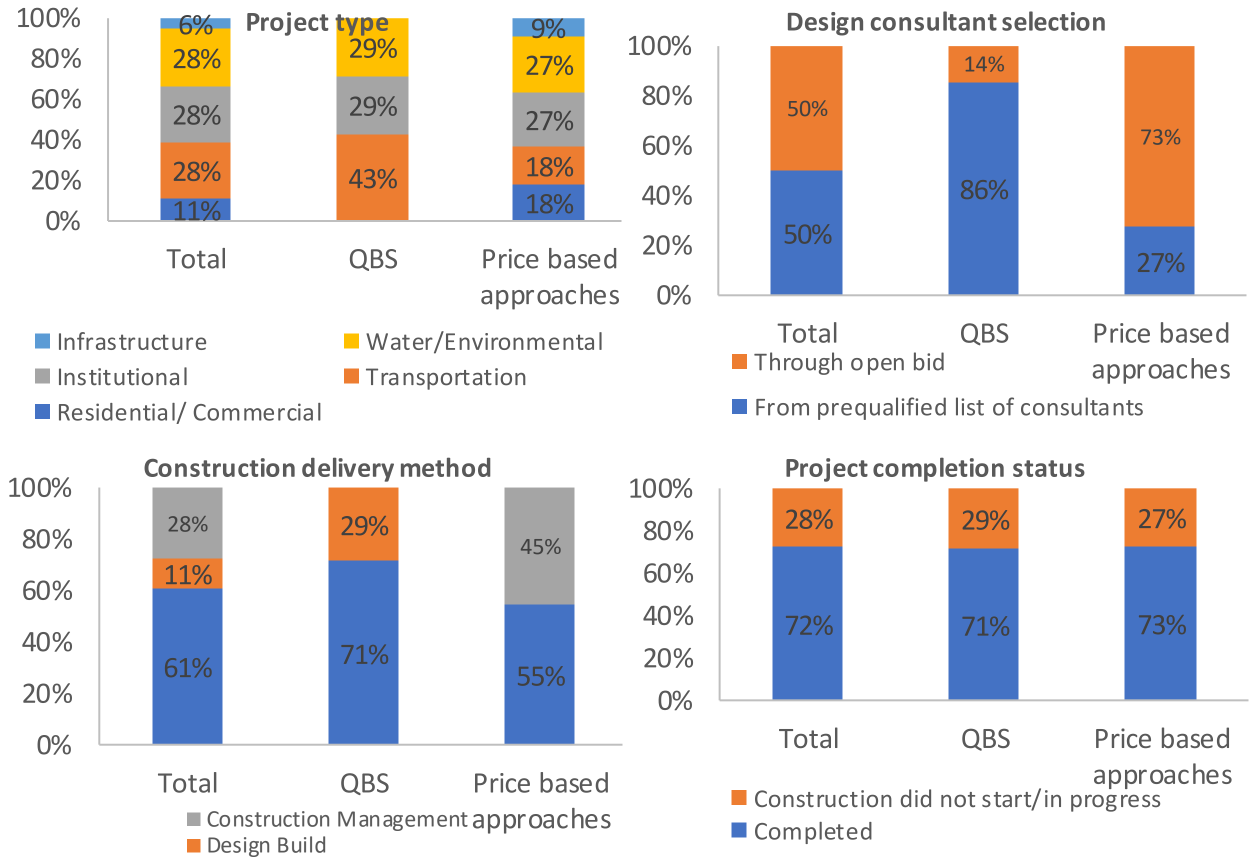

Figure 29. Project demographics

4.4.4 Preliminary analysis of QBS and price-based approaches on project outcomes

Cost and Schedule Indices

As discussed in section 4.4.3, two groups of projects were formed to compare the differences in performance when price is included as an evaluation criterion to when it is not. In this section, we compare Group A (QBS projects) to Group B (price-based approaches) for overall project performance. Since schedule and cost deviations are commonly used to assess project outcomes, part A of the questionnaire was structured to capture actual project time (weeks) and cost ($), as well as the budgeted (planned) costs ($) and completion time (weeks) for both the design and the construction phases.

To measure the deviations related to the design and construction phases, the cost and schedule indices were calculated for each, as shown in equations 7–10. A low-cost index (approaching zero) indicates a less cost overrun, and a negative value reflects cost savings and vice versa. A schedule index is similar but relates to being ahead of or behind schedule. Then the average, standard deviation, maximum, and minimum values were calculated for Group A and B, as shown in Figure 30. For QBS projects, the average design cost is much lower than the average for price-based approaches. Moreover, the maximum values are much lower for QBS projects (40%) as compared to price-based approaches (347%). The maximum values reflect cost overrun for both groups; however, for price-based approaches the actual design fee was more than three times the budgeted fee, even though the minimum value for Group B was much lower, indicating a cost savings. The standard deviation values also showed a larger spread compared to Group A.

The design schedule index is a value in percentage that measures the deviations from the planned completion time and can either be ahead of or behind schedule. The average value for both Group A and B was a positive, which indicated schedule delay for both groups. However, the average value for QBS projects was almost half that of price-based projects, as shown in Figure 31. Also, both the maximum and minimum values for QBS projects were a lower. Overall, Group A design schedule performance was better and showed less schedule delay compared to Group B.

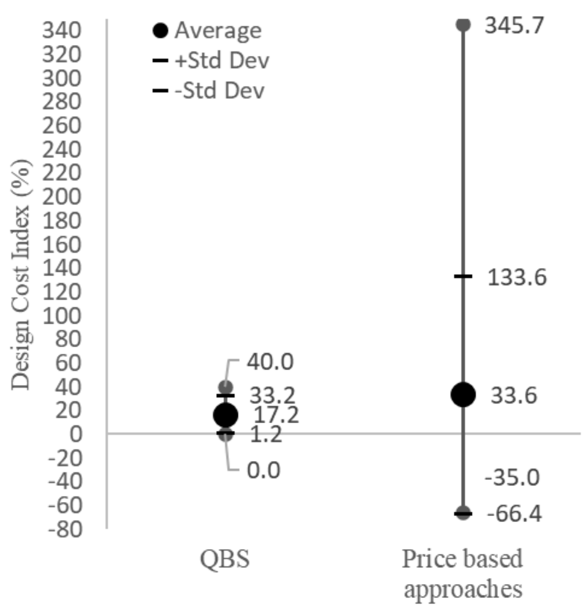

Figure 30. Design Cost Index (%)

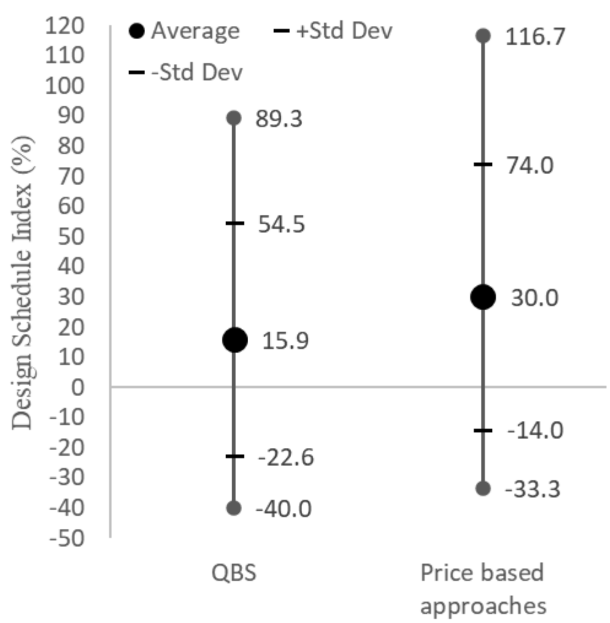

Figure 31. Design Schedule Index (%)

The construction cost index indicates whether the project was above or below the planned budget. The average indices for Group A and Group B are shown in Figure 32. The average value for Group A is negative (–1.3), which means a cost savings. In comparison, Group B had a positive average, indicates cost overrun. The maximum index value of Group A was much lower than Group B, which was almost six times higher than Group A. Also, the standard deviations for Group B were larger compared to Group A. The minimum value for Group A was higher than for Group B, which does not follow the general trends observed for Group A compared to Group B.

The construction schedule index measures the deviations of construction time compared to the planned schedule. The average schedule index for Group A was a bit higher than Group B; therefore, Group B (price-based approaches) had fewer construction schedule delays. However, the minimum value for the schedule index was a bit lower than Group A. The negative minimum value that reflects Group A has some projects finished ahead of schedule. As for the maximum value Group A showed less delay in comparison to Group B, as shown in Figure 33.

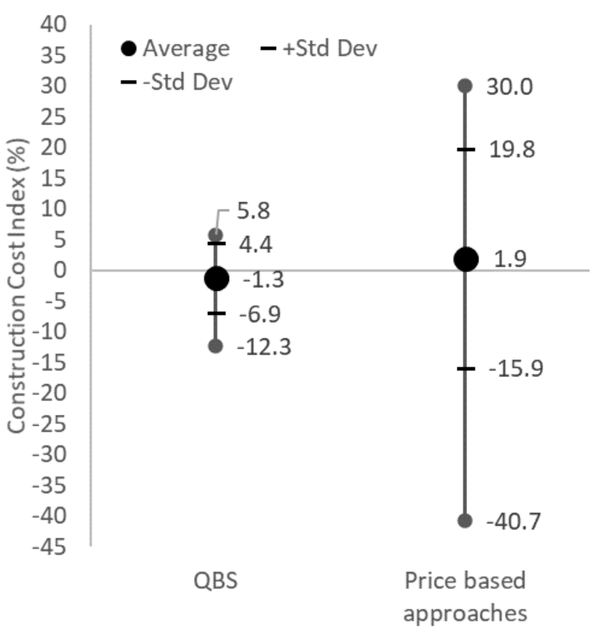

Figure 32. Construction Cost Index (%)

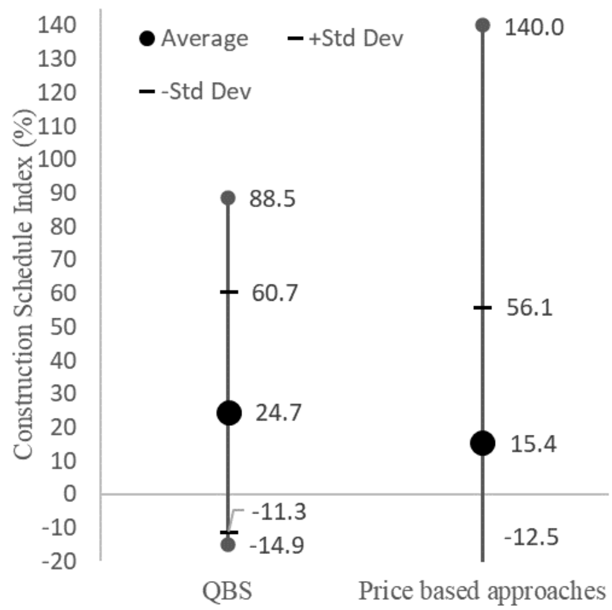

Figure 33. Construction Schedule Index (%)

In general, QBS projects showed better project performance in terms of construction and design cost and schedule compared to price-based approaches projects. However, the average values for the construction cost index minimum and construction schedule index did not follow the general trend. Such anomalies can be attributed to the fact that some of the projects were still under construction; therefore, the actual construction cost and time were missing. Obtaining a sample is an expensive process (given the current circumstances), which necessitated keeping the sample even if it has missing values. The research team decided to substitute missing values using imputation methods, which might have led to some errors. Also, the projects that are still in progress can change their performance as the project advances. Another contributing factor could be that the construction performance is also impacted by the contractor performance and the construction delivery type.

Claims, NCRs, RFIs, and Change Orders

Another measure of project performance is related to change orders, claims, NCRs, and RFIs, and the survey was structured to capture data the number of each. However, numbers alone do not indicate of the impact of change orders and claims on project budget and schedule; therefore, the impact (%) on the actual construction schedule and cost were calculated as per equations 11–14.

$$Impact\ of\ change\ orders\ on\ construction\ cost(\%) = \frac{Impact\ of\ change\ orders\ on\ construction\ Cost\ (CAD)}{Actual\ Construction\ Cost\ (\ CAD)}\ x100 \quad (11)$$

$$Impact\ of\ change\ orders\ on\ construction\ Time(\%) = \frac{Impact\ of\ change\ orders\ on\ construction\ Time(weeks)}{Actual\ Construction\ Time(weeks)} x100 \quad (12)$$

$$Impact\ of\ claims\ on\ construction\ cost(\%) = \frac{Impact\ of\ claims\ on\ construction\ Cost\ (CAD)}{Actual\ Construction\ Cost\ (\ CAD)}\ x100 \quad (13)$$

$$Impact\ of\ claims\ on\ construction\ Time(\%) = \frac{Impact\ of\ claims\ on\ construction\ Time(weeks)}{Actual\ Construction\ Time(\ Weeks)}\ x100 \quad (14)$$

The number of changer orders, NCRs, RFIs, and claims issued throughout the project were a bit higher for QBS projects in comparison to price based approaches (Figure 34). Even though the numbers are not significantly higher, their impacts are important observations. The impact of change orders and claims on construction schedule and cost was captured though the survey questions, then the research team calculated the percentage that the impact had in relation to the actual cost and time. It can be observed that the actual percent impact on construction cost and schedule did not significantly vary between the groups. QBS had slightly higher cost impacts as shown in Figure 35 and Figure 36, but it had lower schedule impact. Comparing the initial performance and how these change orders and claims impacted cost and schedule given the large number shows that these claims and change orders did not have a large impact. However, it can be observed that QBS projects had a lower schedule impact, as shown in Figure 37 and Figure 38.

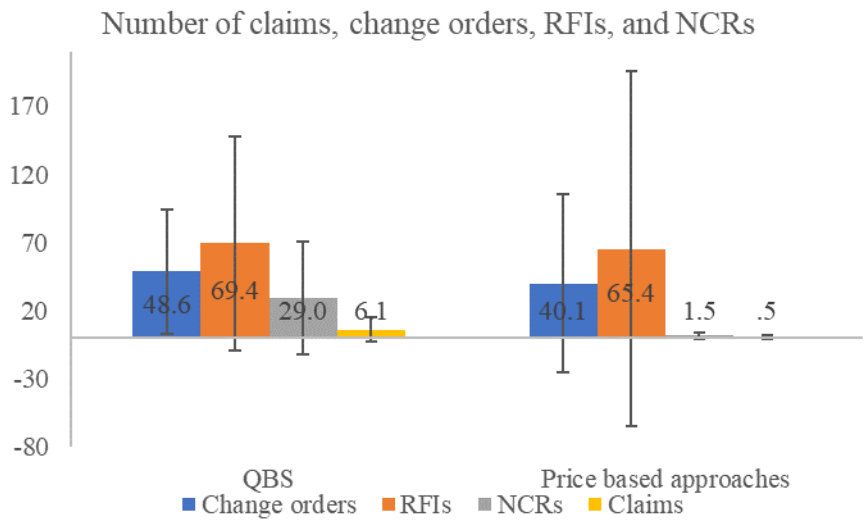

Figure 34. Number of claims, change orders, RFIs, and NCRs

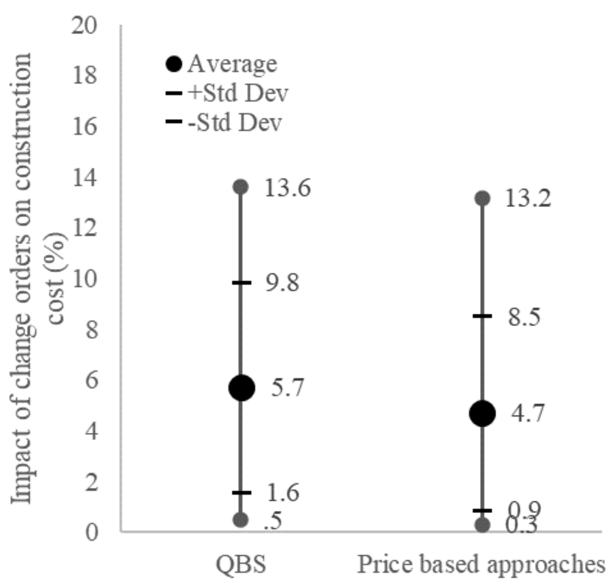

Figure 35. Impact of change orders on construction cost (%)

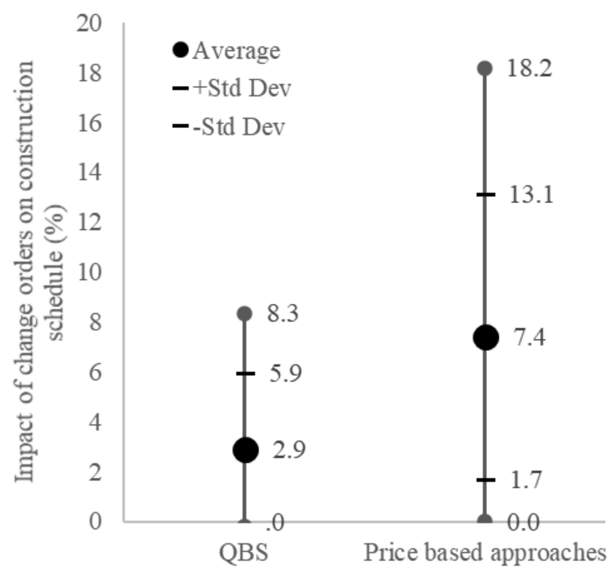

Figure 36. Impact of change orders on construction schedule (%)

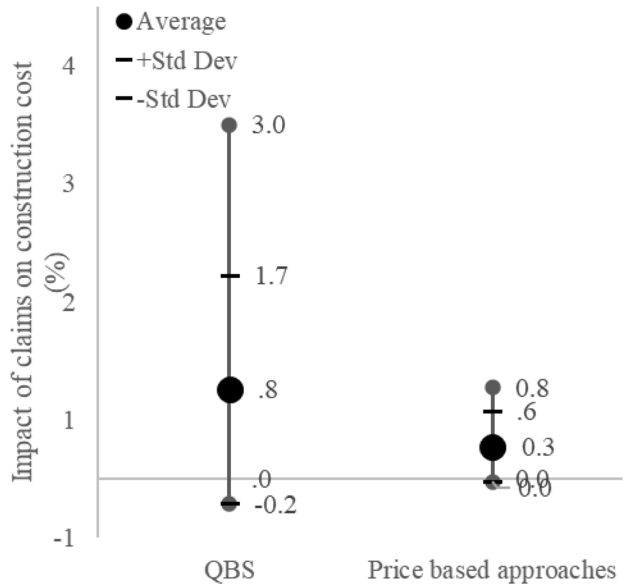

Figure 37. Impact of claims on construction cost (%)

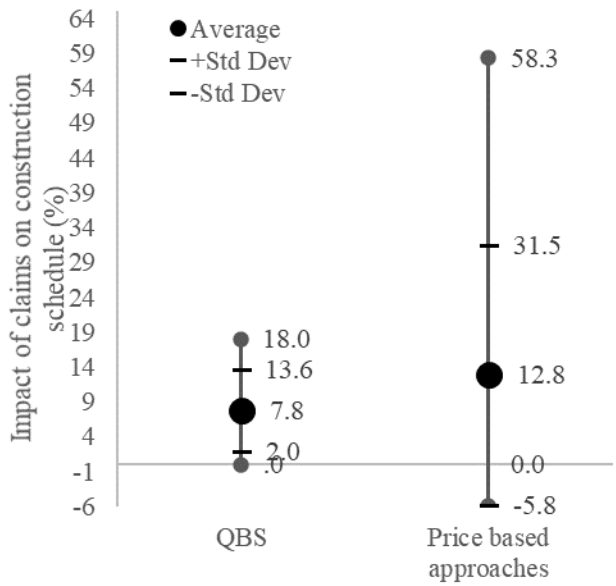

Figure 38. Impact of claims on construction schedule (%)

The Time Associated with Procurement Processes

Another measure of project performance is related to the time associated with the procurement processes, such as the time to select consultant once the bid is made public and the time taken to approve the final design scope, plans, schedule, and fees, as well as the time taken to execute PSAs. The respondents were asked to answer an open-ended question that indicated the duration in weeks. The time for selecting and awarding the consultant and approving the design scope was shorter for QBS than non-QBS projects. For QBS projects, Figure 39 shows that the average time taken to select a consultant once the bid had been made public is 6.6 weeks, which is about 1.5 weeks lower than price-based approaches. Similarly, the maximum value for Group A was 14 weeks less than price-based approaches. The minimum value for price-based approaches is one week lower than QBS, but they are associated with higher deviations.

The time taken to approve the final design scope, plans, schedules, and fees indicates the duration for the submitta, and approval of these documents. As mentioned before, in typical QBS procedure, the scope is usually determined after awarding unlike price-based approaches. Thus, the nature of QBS justifies the slightly higher average (less than one week) compared to price-based approaches

(Figure 40). The minimum value for price-based approaches is 1 week lower than QBS; but they are associated with higher deviations as shown in Figure 40.

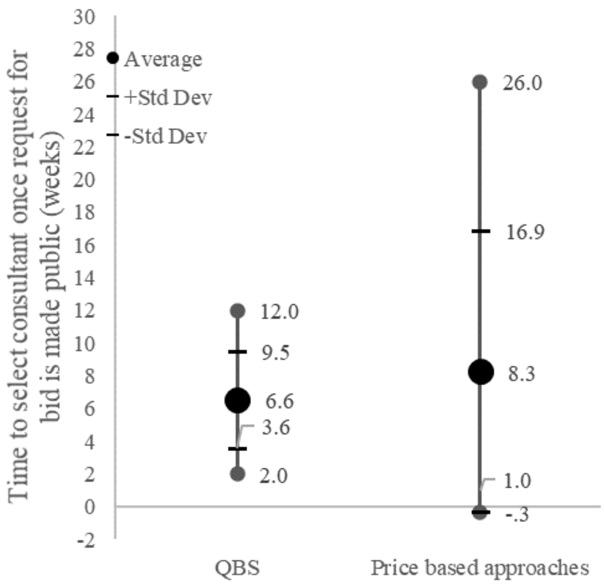

Figure 39. Time to select consultant once request for bid is made public (weeks)

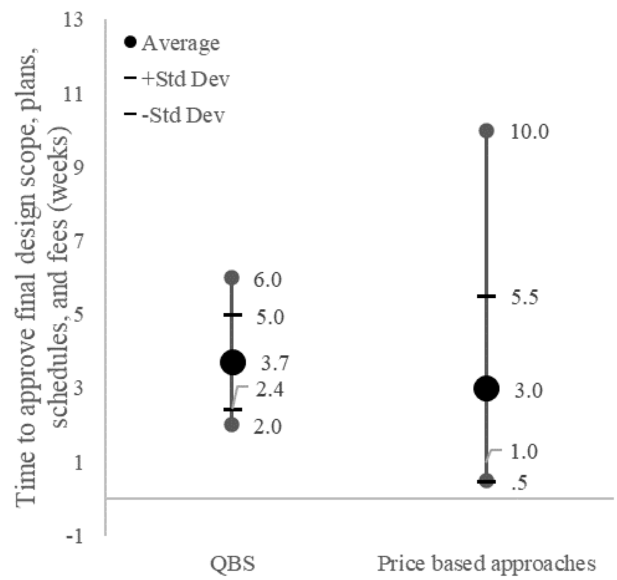

Figure 40. Time to approve final design scope, plans, schedules, and fees (weeks)

The time between selection and awarding was also captured by the questionnaire. The duration includes the time of negotiations and contract signature once the bidder is selected. Based on the plot shown in Figure 41, non-QBS approaches are associated with a higher average compared to QBS approaches (3.6 weeks higher). Furthermore, the maximum value is dramatically higher for price-based approaches as it hikes up to 42 weeks compared to 4 weeks for QBS projects. The minimum is one week for both groups. It can be observed that price-based approaches are associated with more deviations and a higher spread of values that fluctuates between 1–42 weeks, unlike QBS approaches.

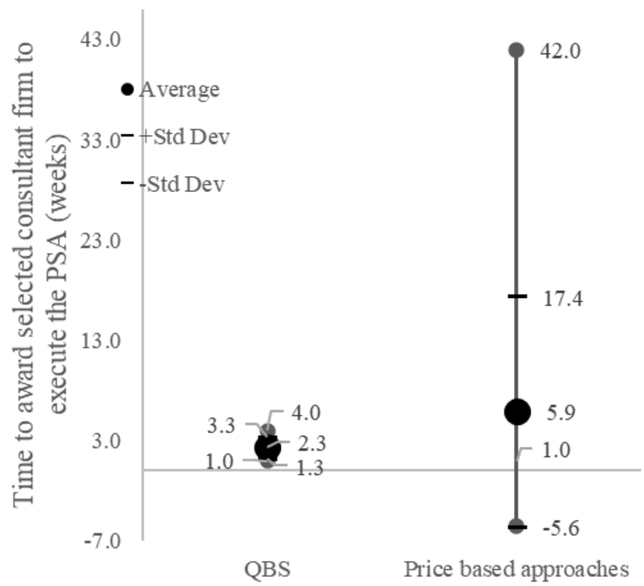

Figure 41. Time to award selected consultant firm to execute the PSA (weeks)

The observed behaviours could be associated to the QBS process, as the owner have the freedom to resort to the second most qualified consultant if the fee negotiation phase were not satisfactory. Unlike price-based approaches, the owner is more bound to award the selected consultant, leads to a longer negotiations period. Furthermore, it could be associated to the previous history between the owner and the consultant. Considering this, the relationship was quantified through two open ended questions that captured the percentage of the organization's projects that were procured to the awarded consultant and the number of years the owner and the consultant worked together. Figures 42 and 43 shows that QBS projects showed superiority in relationship compared to price-based approaches, as the percentage of projects procured and the number of years the owner and the consultant worked together were both higher.

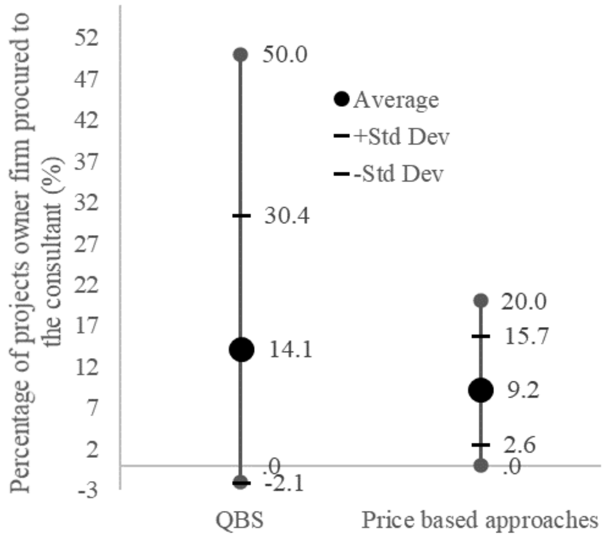

Figure 42. Percentage of projects owner firm procured to the consultant (%)

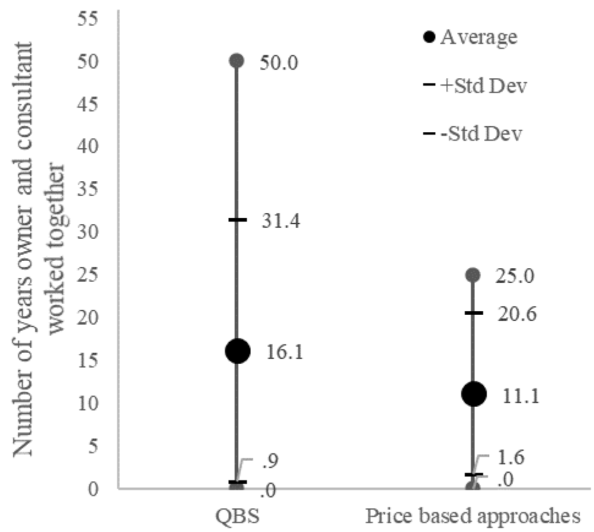

Figure 43. Number of years owner and consultant worked together

Conclusion of the Preliminary Analysis

One major limitation of the analyzed sample is its small size, and it was provided by a limited number of organizations. Also, the research team could not track all the information, as the survey was conducted online to avoid any bias. The presented variables could be associated to the sample behaviour, and a larger dataset would be needed for further statistical significance to decrease bias and uncertainty.

Based on the preliminary analysis, QBS projects generally outperformed price-based approaches in most of the investigated areas. However, one cannot claim such behaviour as a causation of implementing QBS for various reasons. First, a lot of factors can impact project performance more directly than design, such as contractor competence, risks associated with the project, project demographics, and the construction delivery method. Second, there is a lack of information as the research team was not able to track all the information as the survey was conducted online. Third, the sample of projects come from a limited number of organizations which is likes a major source of bias in the project's performance. Therefore, further analysis is required to investigate the correlation between A/E qualifications and project outcomes regardless of implementing QBS as a procurement process, together with investigating the association of other factors, which are the project risks and project demographics/characteristics, such as the construction delivery method, project type, and consultant firm selection (open bid or prequalification).

4.4.4 Correlation Between Project Performance And A/E Qualifications

As discussed before Kendall's and Spearman's correlation coefficients were calculated for the variables; however, Spearman was selected as it resulted in slightly higher results and had literature support. Based on the results presented in Appendix B, the performance indicators related to cost, time, adjustments and changes, compliance, and inquiries all exhibited negative correlation coefficients with the qualifications. This indicates that as the qualifications get higher, these performance indicators would decrease and/or vice versa. However, owner's satisfaction and time associated with procurement process are positively associated with consultant qualifications. This indicates that as the qualifications ranking increases, the satisfaction and time associated with the procurement would increase and/or vice versa. These observations can be summarized as follows.

1- Some of consultant qualifications impact the project performances; these vary depending on which performance indicator is being investigated.
2- There is an inverse relationship between the ranking of some A/E consultant qualifications and some of project performance indicators: cost, time, adjustments and changes, compliance, and inquiries.
3- There is a direct relationship between the ranking of some A/E consultants' qualifications and the time associated with the procurement and owner's satisfaction.

Time and Cost Performance

Based on the conducted analysis, the time and cost overruns for design and construction phases were lower if some of the consultant's qualifications raking were higher. For example, the design cost index decreased when the identification of key personnel's roles and responsibilities, project management experience, and design innovation and value engineering increased. The analysis showed that few explanatory variables related to cost performance affected the accuracy of the validating prediction model, as shown in Chapter 5. This may be because due to projects of different natures or change orders issued during construction. Furthermore, other studies that have tried to predict project costs were not able to accurately predict large cost overruns (William, 2002; Ling and Lui, 2004). As for the schedule performance, schedule overruns are calculated for the construction and design phases. To ensure the punctuality of the design delivery, the consultant should possess a strong health and safety procedure, as well as quality control and sub-consultant experience. Strength in these areas would likely decrease the resubmittal and rejection of some of the design plans; consequently, the overall design schedule overrun would decrease. Furthermore, the strength in cost control is also associated with fewer schedule overruns (for design and construction), which can be explained by the association between time and cost. In other words, a good cost control plan would ensure the timely delivery and the adherence to the schedule to avoid the associated indirect costs. Possessing robust conflict resolution strategies is also essential to ensure a timely delivery in the design phase to avoid the time-consuming process associated with conflicts. Other qualifications are also attributed to a better design schedule adherence, such as the consultant's approach to schedule, budget, and quality control, as well as including experts as a part of the project team.

Changes, Adjustments, and Compliance

Changes and adjustments consume project resources and time. The survey quantified changes and adjustments through soliciting the number of issued change orders and claims, as well as the impact of both on the construction cost and schedule (in CAD and as a 5-point scale from 1–5). The ranking of the number of claims, change orders, and their impacts on construction cost and schedule decreases if some of the qualifications Appendix B gets higher (and vice versa). Appendix B also shows that the number of change orders is contingent on various A/E qualifications, most of which relate to the project comprehension and methodology. However, the number of claims is not strongly associated with consultant qualifications. This may be because the claims can be initiated by any of the parties involved in the project, and the consultant does not control over such initiation. Unlike change orders, design and construction change orders are mainly issued by the owner or to modify some design errors (which is related to the consultant's competence and quality of the submitted documents). The impact of change orders on construction schedule (as a 5-point scale) is associated with more consultant's qualifications, unlike the impact on construction cost. Such observation could be related to the limited control a consultant would have on the cost of the issued variation order. However, when it comes to schedule, the consultant would has a larger say in that matter. Furthermore, the pricing of the variation usually refers to the bid documents (Bill of Quantities). Project management experience, inclusion of experts as part of the project team, understanding of desire project outcomes, and strength of references from clients of relevant projects are common qualification that affect impact of change orders on construction cost and time. Furthermore, three out of the four qualifications areas captured by the survey are highly correlated to the impact of change orders on construction schedule, which are firm qualifications and expertise, project comprehension and methodology, and relevant project experience and past performance. The project team composition and qualifications are not that highly correlated, which could be because team qualifications on their own do not directly affect the impact a change order would have on the schedule. Even though the number of claims is not significantly related with many consultant qualifications, the impact was correlated to various qualifications. This can be because as the consultant gets more qualified, their ability to manage a claim efficiently and to optimize the associated time and cost would increase as well. Consequently, the impacts of such claims on construction cost and time would decrease.

The compliance and inquiries are quantified through capturing the number of NCRs and RFIs. NCRs are issued to address a deviation from the project specification either related to design or construction. NCRs are usually related to quality issues where the work failed to achieve standards and specifications (Rodriguez, 2019). RFIs are usually issued by the contractor to the owner's consultants to inquire about a certain subject manner. Having many RFIs and NCRs is unfavourable as it consumes time and exhaust the project resources. As shown in Appendix B, there is a correlation between some of the qualifications and the numbers of RFIs and NCRs. However, few qualifications correlated to the consultant's competence, which might be because the RFIs and NCRs are usually related to the construction process and not the design.

Owner's Satisfaction and Time Associated with the Procurement Process

As mentioned in Section 4.2, the owner's satisfaction was captured in Part A and Part B of the survey to reflect the satisfaction by the procurement and the management teams assigned to the projects. The reported satisfactions matched with minor ranking differences. Therefore, to avoid repetition in variables, the minimum of both variables was taken, and a new variable "Owner's satisfaction" was created. The owner satisfaction and time associated with procurement exhibited a different trend in comparison to the remaining correlation coefficients, which was a positive correlation coefficient. As the ranking of consultant qualifications increases, the owner's satisfaction and the time associated with the procurement process also increase. A higher satisfaction from the owner side is a favorable performance outcome. Based on the results shown in Appendix B, the consultant should possess strength in some of qualifications to ensure owner satisfaction. Such qualifications vary depending on the required area of satisfaction. For the time associated with procurement, a longer procurement was associated with a higher qualification ranking. One possible explanation could be that as the consultant becomes more qualified, the time taken to produce more accurate designs increases. To support this hypothesis, the number of change orders decreases as the ranking of consultant qualifications increases. In other words, a more qualified consultant would take more time to submit accurate drawings that require a smaller number of adjustments, less errors and consequently a smaller number of change orders during project execution. However, it should be noted that the research team was not able to discuss with the participants the background of some matters, such as the reason for change orders, whether it is an owner-initiated adjustment, or a variation issued to modify a design/construction related error.

4.4.5 Correlation Between Project Characteristics and A/E Qualifications

In the previous section, the correlation between consultant qualifications and project outcomes was been identified. In this section, the correlation between project characteristics and project performance indicators was identified using Spearman correlation coefficient.

As discussed before Kendall's and Spearman's correlation coefficients were calculated for the variables; however, Spearman was selected as it resulted in slightly higher results and had literature support. Based on the results presented in Appendix B, some of the project characteristics impact the project performance and these vary depending on which performance indicator is investigated. However, it should be noted that the research team was not able to discuss with the participants the background of some matters, such as the reasons associated with the project performance such as cost and schedule overruns. This section will suggest a possible reasoning for the observed behaviour.

Time and Cost Performance

Based on the conducted analysis, the design and construction indices were correlated to the earlier identified project characteristics. Some of the characteristics showed an inverse relationship with the indices, and others showed a direct relation.

The design cost index showed a positive correlation coefficient with the risk of working with the consultant firm. In other words, the index will get higher as the risk of working get higher or vice versa. This was expected behaviour since a higher risk associated to working with the consultant can eventually lead to design cost overruns as the project progresses due to lack of consultant competence. The design cost index correlated negatively with the design technical complexity, interdependencies of construction trades and tasks, sustainability aspects, and human factors for employees during the construction process. The design technical complexity showed an inverse relationship with the design cost index, which could be associated to the qualifications of the awarded consultant. To illustrate, when one of the project characteristics has high technical complexity, that could urge the procurement team to select a highly qualified consultant; therefore, the awarded consultant was able to give a good estimation for the design fee and further control as the project progresses. That could also be a possible reason for the inverse relationship between the design cost index and the other variables mentioned above.

Various project characteristics were positively correlated to the design schedule index. Like the design cost index, risk with working with the consultant firm was correlated to the design schedule index with a positive coefficient. The technical complexity, interdependencies of construction trades and tasks also showed a direct relationship, unlike design schedule index. This behaviour could be associated to some lack of control regarding managing the project schedule. Therefore, as the technical complexities and interdependencies of construction trades and tasks increase, the design schedule index will increase as well, and vice versa. Other variables that were correlated in a direct relationship with the design schedule index are project cost related complexity, number of firms collaborating in the project, and consultant firm selection. As the project cost complexity and/or the number of firms collaborating increase, the design schedule increases, and vice versa. This is an expected behaviour because many firms collaborating on a project would consume time, thus impacting the design schedule required to coordinate them. Also, the consultant firm selection indicates whether the consultant firm is selected from an open bid or a prequalified list of consultants, thus impacts the design schedule.

Like the impact of qualifications, few project characteristics showed a correlation with construction cost and schedule indices. Location based complexity is inversely correlated to the construction cost index, as well as human factor for employees during the construction process. One of the possible explanations of such behaviour would be that the project team would invest more time to produce an accurate estimate and control through the project construction execution when there is a high complexity related to the project location or with the employees' impact on the project, and vice versa. This could eventually lead to cost overrun as the project progresses.

Also, the consultant firm selection showed a positive correlation coefficient with construction cost overrun.

Construction cost index is correlated to project cost related complexity, community impact, and the end users. Based on the investigated sample, the construction schedule index decreased as the cost complexity increased. Like the above, this could be related to the amount of planning that the project team puts in when one of the project characteristics is cost complexity. Furthermore, as the community impact increased, the construction schedule index and the end user impact increased, and vice versa.

Changes, Adjustments, and Compliance

Changes and adjustments consume project resources and time. The survey quantified the changes and adjustments through soliciting the number of issued change orders and claims, as well as the impact of both on the construction cost and schedule (in CAD and as a 5-point scale from 1–5). The number of claims and change orders, along with the ranking of their impacts on construction cost and schedule, increased as some of the ranking of the project associated risks and social factors increased (and vice versa), as described Appendix B. The number of change orders is attributed with the risk of completing the project on budget and time, political risks, complexity of project requirements, cost related complexity, number of firms collaborating in a project, interdependencies of the construction trades, design procurement method, and the consultant firm selection. All these variables showed a positive correlation with the number of change orders. One reasonable explanation is that as the risk and social factors impacting a project increased, the adjustments and issued variations also increased, and vice versa. However, few variables were correlated with the impact of these change orders on construction cost and time.

Like the impact of qualifications, the number of claims was associated with few project characteristics. This might be because claims can be initiated by any of the parties involved in the project, regardless of the project's characteristics. The impact of such claims on construction cost and time was correlated with the design procurement method, consultant firm selection, and construction delivery method. Other characteristics also contributed to impact of claims on construction cost, which are risk with working with consultant firm and complexity of project requirements. Project type and the employees' impact during construction showed a correlation with impact of claims of construction time.

Compliance and inquiries were quantified through capturing the number of NCRs and RFIs. They were positively correlated with location-based complexity, cost related complexity, design procurement method, and construction firm selection. They were correlated with other variables, as illustrated in Appendix B.

Owner's Satisfaction and Time Associated with the Procurement Process

As mentioned in Section 4.3.4, owner satisfaction was captured in Part A and Part B of the survey to reflect the satisfaction by the procurement and the management teams assigned to the projects. The reported satisfactions match with minor ranking differences. Therefore, to avoid repetition in variables, the minimum of both variables was taken, and a new variable "owner satisfaction" was created. Owner satisfaction was correlated to some of the project's risks, attributes, design complexity, and social factors, as listed in Appendix B. For the time associated with procurement, the longer procurement time is associated with higher risk ranking, some of the solicited social factors, and the design complexity. Also, the construction delivery method and design procurement method are correlated to procurement time.

4.5 Summary

This chapter outlined the impacts of A/E consultant qualifications and project characteristics on project performance indicators. The design of the questionnaire, the required dataset, and the development of the correlation model were explained in Section 4.3. To implement the proposed model, a case study of 18 projects (questionnaire responses) was studied. The solicited responses were preliminarily analyzed to understand the behaviour of projects when price was or was not a selection criterion to award the A/E consultant. Projects where price was not included outperformed the other group (price-based approaches), as illustrated in section 4.3.3. CA using Spearman and Kendall correlation coefficients was then employed to study the relationship between consultant's qualifications, project characteristics, and project performance. Some of the studied qualifications and project characteristics are correlated to the performance indicators. Possible reasoning of such correlation was presented in Section 4.4. In the following chapter, a model is developed to verify and validate the captured correlations.

CHAPTER 5. VERIFICATION AND VALIDATION OF THE CORRELATION ANALYSIS USING PREDICTION MODEL

5.1 Introduction

After studying the relationship between A/E consultant qualifications, and project characteristics with project performance indicators, two validation and verification methods were implemented to validate the performance of the model and the process: face validation and predictive validation (Sargent, 2007). Face validation is explained in Section 5.4. For the predictive validation, the output of the correlation analysis (subset features) are the model inputs, and the project performance metrics are the output. The actual and forecasted values are then compared, and the errors percentages are calculated to measure the accuracy of the model performance. First, the association between the consultant qualifications and project performance indicators were validated to avoid any influence other variables might have on the indicators. Then, the project characteristics were the input to another validation model to validate their impact on project performance indicators. Lastly, a model that integrated the earlier identified consultant qualifications and the project characteristics was developed. The purpose of this model is to make it realistic, as project characteristics and risks and the consultant qualifications are an inherent aspect of any project. The integrated model could be used by owners to predict performance indicators based on project characteristics and A/E consultant qualifications. In this chapter, the development of the models is presented along with a case study that implements the suggested model.

To summarize, this chapter addresses the following:

1- The development of the predictive validation model.
2- Validation of the case study outputs presented in Chapter 4.

5.2 Predictive Validation Model Development

A model is developed to confirm the output of the correlation analysis. In this regard, a prediction model has been developed where the output list of consultant qualifications and project characteristics are the model inputs. The purpose of such model is to predict the performance outcomes based on the consultant qualifications and project characteristics. An acceptable prediction performance would then indicate that these variables are correlated to the performance indicators and vice versa. The model development process is shown in Figure 44. First, the list of qualifications that were the output of the correlation analysis were input to a prediction model to validate the correlation between consultant qualifications and project performance. Next, the list of project characteristics was input to another prediction model to confirm the correlation between the project characteristics and project performance. Finally, the characteristics and performance indicators were the input to a third prediction model to make the model more realistic. This model could be used by owners to predict project performance based on consultant qualifications and project characteristics.

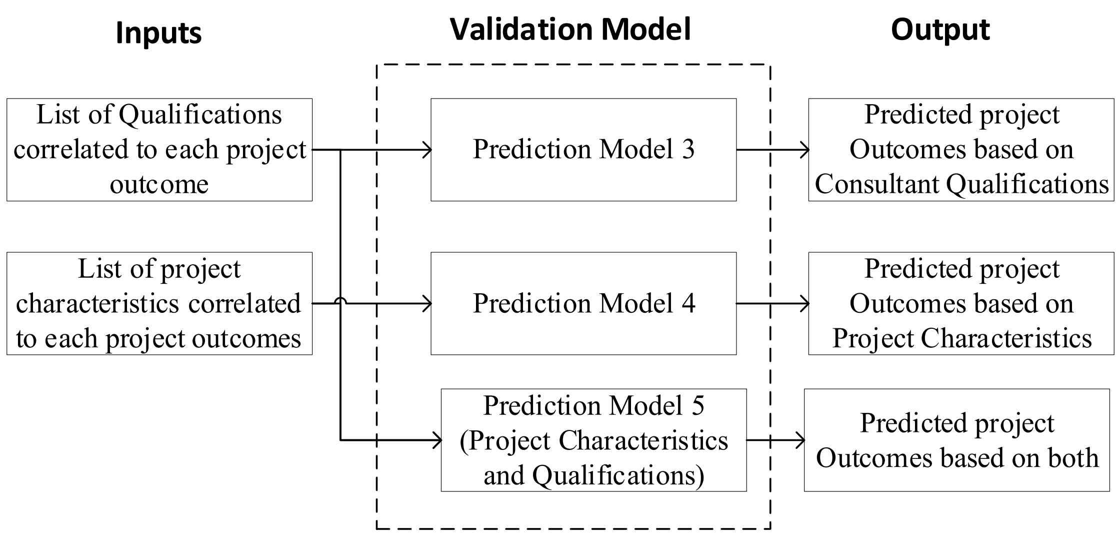

Figure 44. Validation model process

ANN was used to validate the output of the correlation analysis and to check the accuracy of the explanatory variables in predicting the performance indicators (Ling and Liu, 2004). The output of the correlation analysis is the input to the prediction model to validate the significance of the A/E consultant qualifications ranking, as well as project characteristics in predicting the project performance.

5.2.1 Dealing with multicollinearity

Multicollinearity problems occur due to high correlation between predictors (independent variables) and can lead to errors in model behaviour (Garg, 2012). Therefore, such an issue can be tackled through using Factor Analysis (FA) and variable reductions methods (Garg, 2012). Such methods are more applicable when using modeling methods Fuzzy Logic (FL), as they do not inherently automate feature selection (Garg, 2012).

In our dataset, multicollinearity is inherent to the process being studied. For example, the consultant qualifications section in the survey was divided to assess different qualifications such as firm's qualifications and experience, project team composition and qualifications, etc. For each of these qualifications the survey was designed to capture several inputs that are inherently correlated. To illustrate, firm qualifications and experience are divided into several elements, which are project management, project control, health, and safety processes, etc. Therefore, ANN was the selection prediction method as it fits the dataset where multicollinearity exists (Goodarzi et al., 2009; Noori et al., 2010).

5.2.2 Bootstrapping

One of the major challenges in implementing the proposed methodology is data scarcity due to confidentiality, sensitivity, and the time needed to provide the requested data. However, to train a prediction model, many projects are required. Bootstrapping can help to overcome data scarcity. Bootstrapping is a procedure that involves random resampling of the existing dataset with replacement (Sonmez, 2011). Sampling with replacement indicates that every sample is returned to the dataset after sampling. For example, a sample (a project) might appear zero, one, two, or more times bootstrap sample. Bootstrapping can be used to achieve a level of certainty in the sample parameters, and it can be also used to improve the prediction performance of ANNs when there is a small dataset for training (Tsai and Li, 2008). The purpose of bootstrapping is to mimic the process of observation sampling through resampling from the original dataset (Efron and Tibshirani, 1993). For this study, one of the major limitations was the data collection process. These challenges were due to the unique nature of this research, as well as the pandemic that led to challenges in collecting more data. Consequently, the current sample size is 18 projects with complete survey responses and is not sufficient for the training process of the classifier. Therefore, bootstrapping with replacement has been used to produce 250 samples to train and test the ANN. Using the bootstrapping has been shown to enhance the prediction performance and will be discussed in Section 5.3. Also, this chapter presents a case study on implementing the proposed method; however, the performance of the model would be enhanced when more data are available.

5.2.3 Artificial Neural Networks (ANNs)

ANN modelling was chosen because of its strength regarding the learning capability and its ability to produce fairly accurate estimates, even if the given information is incomplete. Also, given the complex nature of the relationship between the investigated variables, the literature suggested using ANNs. The ANN consists of three elements, the input, output, and hidden layers. The input layer has one or more neurons (nodes) that represent the independent variables as identified by the correlation analysis in section of Chapter 4 (X1, X2, …). The output layer also consists of nodes that represent the dependant variables, which are the project performance indicators in this study. For this study, 22 models (Y1, Y2, …, Y22) were created for each performance indicator, covering the six sectors of the project performance: time, cost, adjustments and changes, compliance and inquiries, time associated with the procurement, and owner's satisfaction (shown in Appendix B). The output layer represents the model outcome classification decisions. The hidden layers connect the output and input layers, and one or more hidden layers can be present. The number of hidden layers is identified by the user, as is the number of nodes in each layer. The user would identify the number of hidden layers and nodes of each hidden layer based on a trial and error to achieve the desired accuracy.

5.2.4 Validating the correlation between A/E qualifications and project performance (Model 3)

The ranking of A/E consultant qualifications are the only input (dependent variables) for this model. The purpose of this section is to validate the correlation between consultant qualifications and the project performance without any bias by other variables. An ANN was used to validate the output of the correlation analysis and to check the accuracy of the explanatory variables in predicting the performance indicators. The number of nodes for each layer varies for each model depending on the optimized accuracy measures for the model. The process of this model is shown in Figure 45.

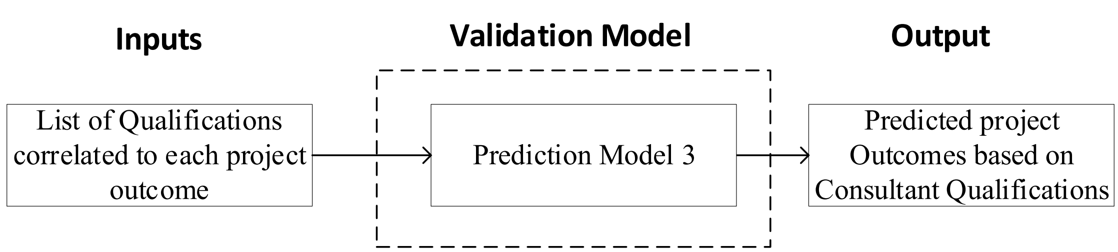

Figure 45. Process for validation model (Model 3)

Model Input

The ranking of consultant qualifications relative to each performance indicator (output of the correlation analysis) was input to the prediction model. Consultant qualifications were ranked on a 5-point ordinal scale, as described in Section 4.2. The data needed to be processed via the bootstrapping procedure to enhance the training stage of the ANN model. Since each of the identified 22 performance indicators (shown in Appendix A) is correlated with a different set of consultant qualifications, 22 validation models were built for each.

Process

The processing of the inputs was undertaken using *R-Studio* software (Version1.2.5033, RStudio Team, 2020), and the programming language used was *R*. *R-Studio* was selected due to its robust capability and its common use in research. A feed-forward ANN was used with a neural net package in *R-Studio*. The number of hidden layers was identified by the user, along with number of nodes in each layer. Also, cross validation was implemented with *K* number of folds. Cross validation was chosen since the nature of the data makes each data point expensive; therefore, it was selected to make the best use of the data in training and testing. A sample of the source code is shown in Appendix C.

Model Output

The output of the model is the predicted performance outcomes, which includes the 22 performance indicators as shown in Table 7. For each model, the predicted project performance (Predicted Y) was calculated based on the ANN model which was compared to the actual performance (Actual Y) to calculate the accuracy of the prediction models. The performance of the prediction models was measured by comparing the actual value to the predicted values by calculating the PE, MPE, MAPE, RMSE and RSE (equations 15–19).

1. Percentage Error (PE)

$$PE = \frac{(Actual\ Value - Predicted\ Value)}{Actual\ Value} \text{ x } 100\ \% \qquad (15)$$

2. Mean Percentage Error (MPE)

$$MPE = \frac{\sum_{i=1}^{n} PE}{n}, \text{where } n \text{ is the number of predictions} \qquad (16)$$

3. Mean Absolute Percentage (MAPE)

$$MAPE = \frac{\sum_{i=1}^{n} |PE|}{n}, \text{where } |PE| \text{ is the absolute value of the percentage error} \qquad (17)$$

4. Mean Square Error (MSE)

$$MSE = \frac{\sum_{i=1}^{n}(Actual\ value - Predicted\ value)^2}{n}, \tag{18}$$

5. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{MSE} \tag{19}$$

Table 7. Performance indicators

No.	Performance Indicators	Description
		Cost
Y1	Design Cost Index (%)	[(Actual Design Fee - Budgeted Design Fee)/ Budgeted Design Fee] *100
Y2	Construction Cost Index (%)	[(Actual Construction Cost - Budgeted Construction Cost)/ Budgeted Construction Cost] *100
		.
		.
		.
Y22	The resulting project quality and contractor performance were satisfactory	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
		Time
Y3	Design Schedule Index (%)	[(Actual Design Time - Budgeted Design Time)/ Budgeted Design Time] *100
Y4	Construction Schedule Index (%)	[(Actual Construction Time - Budgeted Construction Time)/ Budgeted Construction Time] *100

5.2.5 Validating the correlation between project characteristics and project performance (Model 4)

The project characteristics are the only input (dependent variables) for this model. The purpose of this section is to validate the correlation between the project characteristics and the project performance without bias by other variables. An ANN was used to validate the output of the correlation analysis and check the accuracy of the explanatory variables in predicting the performance indicators. The number of nodes for each layer varies for each model depends on the optimized accuracy measures for the model. The process of this model is as shown in Figure 46.

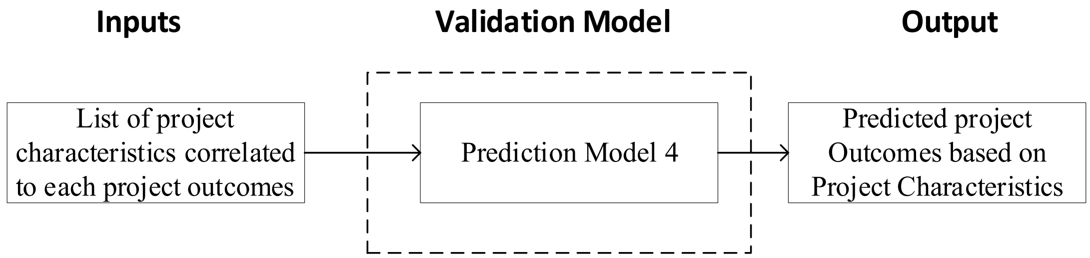

Figure 46. Process for validation model (Model 4)

Model Input

The project characteristics related to each performance indicator (output of the correlation analysis) were input to the prediction model. The project characteristics are explained in Section 4.2.1. The data needed to be processed via the bootstrapping procedure to enhance the training stage of the ANN model. Since each of the identified twenty-two performance indicators (some of which are shown in Table 7 and the rest in Appendix B) is correlated with a different set of project characteristics, 22 validation models were built for each.

Process

A similar process is implemented as shown in section 5.2.4. A sample of the source code is shown in Appendix C.

Model Output

The output of the model is the predicted performance outcomes as shown in Table 7, Appendix A, and Appendix B. For each model, the predicted project performance (Predicted Y) was calculated based on the ANN model and compared to the actual performance (Actual Y) to calculate the accuracy of the prediction models. The performance of the prediction models was calculated by comparing the actual value to the predicted values by calculating the PE, MPE, MAPE, RMSE and RSE (equations 15–19), shown in Section 5.2.4.

5.2.6 Integrated Model to predict the project performance outcomes based on A/E qualifications and project characteristics (Model 5)

After validating the relationship between the project characteristics, and A/E consultant qualifications on performance outcomes, an integrated model was developed. This model combined the list of qualifications and project characteristics that were correlated to each performance outcome. This model could be used by owners to predict the performance outcomes of a project depending on project characteristics and A/E consultant qualifications. The number of nodes for each layer varied for each model depending on the optimized accuracy measures for the model. The process of this model is as shown in Figure 47.

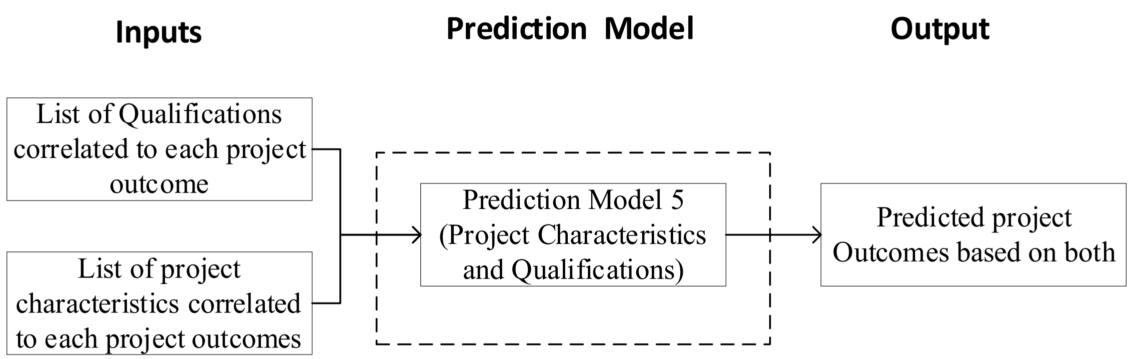

Figure 47. Process for prediction model (Model 5)

Model Input

The project characteristics and ranking of the A/E qualifications were the input to this model to capture the interactions between these variables and their impact on project performance outcomes. The list of qualifications and project characteristics related with the project performance indicators were obtained through the correlation analysis.

Process

Similar process is implemented as shown in section 5.2.4. A sample of the source code is shown in Appendix C.

Model Output

The output of this model is the predicted project performances based on the project characteristics as well as the A/E consultant qualifications. These performance indicators are as shown in Appendix A.

5.3 Case Study

This section covers the validation the case study findings that were presented in Section 4.4. Also, it includes the application of the proposed prediction model and compares the accuracy of three models.

5.3.1 Validating the correlation between A/E qualifications and project performance (Model 3)

We used the ranking of A/E consultant qualifications as the only input (dependent variables) for these models. However, we obtained good predictions given our dataset and not including other variables such as project characteristics, consultant-owner relationship, etc. A two-layered, feed-forward ANN model was deemed to be the optimal structure. Furthermore, to enhance the learning performance, cross validation was employed where the number of folds applied was 40. The MAPE of 14 out of the 22 models were less than 35%, which can be an indication that these models have an acceptable prediction capability. A discussion of this model follows. It could be observed that the performance of this model was generally better than (lower MAPE) solely using project characteristics as input variables as shown in section 5.3.2.

Time and cost performance

Cost performance was quantified through calculating the design cost index (*Y1*) and the construction cost index (*Y2*). To validate the correlation between the consultant's qualifications (as shown in Appendix B) and these indicators, an ANN model was employed. In other words, the purpose of implementing the ANN model was to measure the significance of the correlation between the consultant's qualifications and the performance indicators. Such significance was quantified through the prediction performance of the ANN model. For example, the design cost index (%) is correlated to three consultant qualifications, which are the project management experience, identification of key personnel's roles and responsibilities, and design innovation and value engineering. These three variables were the input to the prediction model where the design cost index is the predicted value (model output). The MAPE of the two models: design cost index and construction cost index are 50.5% and 68.72%, respectively, as shown in Table 8. The MAPE shows that both can not be accurately predicted (both exceeded 50%). The cost performance of construction project is of a complex nature as it is affected by various factors and each project would be considered unique of different nature and usage. However, the RMSE for these models are about ±13% accuracy. Thus, the ranking of the consultant's performance is deemed not sufficient to solely predict the cost performance in the design and the construction phases of the project.

The MAPE for the time performance design schedule index (*Y3*) and construction schedule index (*Y4*) were 7.34% and 28.06%, respectively, which can indicate an acceptable prediction performance (Table 8). This indicates that the ranking of some of the A/E consultant qualifications are significantly associated to the time performance of the project. This can be because the consultant competence can help to ensure the timely delivery of the design and construction phases of the project.

Table 8. Cost and time models performances prediction performance (Model 3)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y1	Design Cost Index (%)	3	20	40	25.34	50.5	13.6	185.18
Y2	Construction Cost Index (%)	3	80	20	50.34	68.72	13.45	180.98
Y3	Design Schedule Index (%)	7	70	40	6.8	7.34	45.09	2033.42
Y4	Construction Schedule Index (%)	4	60	40	5.71	28.06	0.62	0.38

Adjustments, claims and compliance

As mentioned before, the claims and compliance were identified through capturing the number of change orders, claims, NCRs, RFIs, and the impact of claims and change orders on construction cost and time. The number of NCRs and RFIs is deemed poorly associated to the ranking of the consultant's qualifications; therefore, it was excluded. (The MAPE exceeded the 100%.) In addiction, the number of claims and change orders models possess poor prediction performance, 77.87% and 77.8%, respectively (Table 9). This indicates that the ranking of consultant qualifications cannot solely predict these numbers. The impact of change orders and claims on construction cost and schedule have a relatively acceptable MAPE, all below 30% as shown in Table 9. That indicates that the correlation analysis output is validated through the ANN models employed for these variables. Therefore, the consultant qualifications are deemed significant in regard to their impact on predicting the impact of change orders and claims. As illustrated in Section 4.4, that the correlation is negative: as the ranking of consultant qualifications increase, the impact of change orders and claims on construction cost and time would decrease and vice versa.

In conclusion, the ranking of the consultant qualifications can not exclusively predict the number of RFIs, NCRs, change orders, and claims. However, the impact of claims and change orders on construction cost and schedule can be predicted using the consultant qualifications solely as the input to the ANN model.

Table 9. Adjustments, claims and compliance prediction performance (Model 3)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y5	Number of Change Orders	10	70	40	10.34	77.87	50.32	2532.39
Y6	Impact of Change Orders on Construction Cost	7	80	40	4.31	25.46	0.76	0.59
Y7	Impact of Claims on Construction Cost	10	80	80	26.61	40.81	0.692	0.478
Y8	Number of Claims	3	10	70	39.47	77.88	5.48	30.07
Y9	Impact of Change Orders on Construction Schedule	17	20	70	5.35	18.68	0.66	0.44
Y10	Impact of Claims on Construction Schedule	8	20	70	3.5	18.28	0.74	0.55

Time associated with procurement and owner's satisfaction

The time associated with procurement includes the time taken to select the consultant once the bid has been made public; the time taken to approve the designs, plans, etc.; and the time taken to award the consultant. The MAPE of each is 29.66%, 25.07%, and 30.76% (Table 10), respectively, which can be considered an acceptable prediction performance. This validates the correlation and the significance between the ranking of consultant qualifications and the time associated with the procurement process. Moreover, the good performance related to predicting the time associated with the procurement process could be related to the number of input variables (23 variables).

Owner's satisfaction was identified through capturing the ranking of seven areas by the participants. The MAPE of one satisfaction area, "the procurement process used a competitive and cost-effective process", exceeded 100%; therefore, it was excluded. Also, the procurement approach, "promoted innovation and capacity building satisfaction model", yielded high MAPE as shown in Table 10, which indicated a poor prediction performance. However, all the other five satisfaction areas resulted in a reasonably acceptable MAPE, which indicates good prediction performance. This can imply that the owner satisfaction can be solely associated to the qualifications of the A/E consultant.

Table 10. Time associated with procurement and owner satisfaction prediction performance (Model 3)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y13	Time taken to select the consultant firm once a request for a bid has been made public	23	10	70	9.72	29.66	4.73	22.44
Y14	Time taken to approve the final design scope, plans, schedule, and fees	23	10	70	4.04	25.07	1.53	2.34
Y15	Time taken to award the selected consultant to execute the PSA	23	10	70	13.98	37.76	6.35	40.38
Y17	The selected procurement approach enhanced project effectiveness	7	10	70	4.03	16.59	0.85	0.73
Y18	The benefits of the procurement process outweighed associated risk	4	10	70	7.44	16.84	0.82	0.67
Y19	The process addressed incomplete scope	3	10	70	3.1	35.04	1.34	1.81
Y20	The procurement approach promoted innovation and capacity building	10	10	70	7.18	15.75	0.7	0.5
Y21	The resulting design concept and consultant performance were satisfactory	12	10	70	73.56	73.56	3.06	9.37
Y22	The resulting project quality and contractor performance were satisfactory	17	10	70	2.16	7.25	0.66	0.44

5.3.2 Validating the correlation between project characteristics and project performance (Model 4)

In this model the project performance indicators were predicted using the project characteristics as identified by the correlation analysis. The accuracy of the prediction model is presented in this section. The case study findings presented in Section 4.3.5 are validated in this section. The list of project characteristics correlated to the performance indicators are shown in Appendix B. It could be observed that the performance of this model was generally worse than (higher MAPE) solely using A/E consultant qualifications as input variables as shown in section 5.3.1.

Time and cost performance

The construction cost and schedule indices were correlated to some project characteristics; however, having them as the only input to the prediction model did not achieve an acceptable MAPE, as both exceeded 100%. As for the design cost and schedule indices, the MAPE was 50.5% and 67.8%, respectively as shown in Table 11. It shows that both can not be accurately predicted; both exceeded 50%. This could indicate the project characteristics are not enough to predict the cost and schedule construction and design indices. The cost performance of construction project is of a complex nature as it is affected by various factors, and each project of different nature and usage.

Table 11. Cost and time models performances prediction performance (Model 4)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y1	Design Cost Index (%)	3	20	40	25.34	50.5	13.6	185.18
Y3	Design Schedule Index (%)	7	10	40	53.3	67.8	8.19	67.23

Adjustments, claims and compliance

The claims and compliance were identified through capturing the number of change orders, claims, NCRs, RFIs, and the impact of claims and change orders on construction cost and time. The performance measures are shown in Table 12. The number of RFIs was poorly associated to the ranking of the project characteristics; therefore, it was excluded. (The MAPE exceeded the 100%.) The MAPE for predicting impact of claims on construction schedule was about 23%. This could indicate the significance of the correlation between the project characteristics on the impact of claims on construction schedule. As for the remaining indicators, they all exceeded 35% which could indicate that the project characteristics are not enough to indicate the performance in terms of the adjustments and claims.

Table 12. Adjustments, claims and compliance prediction performance (model 4)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y5	Number of Change Orders	8	80	40	29.68	42.18	49.20	2420.92
Y6	Impact of Change Orders on Construction Cost	2	80	40	14.88	37.89	0.91	0.83
Y7	Impact of Claims on Construction Cost	5	80	80	13.35	35.05	0.67	0.45
Y8	Number of Claims	2	10	70	28.76	80.01	6.37	40.64
Y9	Impact of Change Orders on Construction Schedule	3	20	70	5.83	40.79	1.04	1.08
Y10	Impact of Claims on Construction Schedule	5	20	70	4.68	23.93	0.73	0.54
Y11	Number of NCRs	6	10	70	17.4	44.45	17.9	320.5

Time associated with procurement and owner's satisfaction

The time associated with procurement include time taken to select the consultant once the bid has been made public; the time taken to approve the designs, plans, etc.; and the time taken to award the consultant. The MAPE of each is 42.71%, 89.36%, and 79.94% (Table 13), respectively. It could indicate that project characteristics can not solely predict the procurement process time.

As for owner satisfaction, it included the ranking of seven areas as shown in Table 13. Based on the dataset, six out of the seven satisfaction areas had a MAPE below 35%, which could indicate that project characteristics could be predictive of owner satisfaction.

Table 13. Time associated with procurement and owner satisfaction prediction performance (Model 4)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y13	Time taken to select the consultant firm once a request for a bid has been made public	5	10	70	22.53	42.71	5.29	27.76
Y14	Time taken to approve the final design scope, plans, schedule, and fees	4	10	75	42.15	89.36	2.98	8.92
Y15	Time taken to award the selected consultant to execute the PSA	23	10	70	7.95	79.94	8.45	71.84
Y16	The procurement process ensured a competitive and cost-effective process	5	10	70	5.36	7.24	0.518	0.26
Y17	The selected procurement approach enhanced project effectiveness	4	10	70	4.06	31.51	1.55	2.42
Y18	The benefits of the procurement process outweighed associated risk	4	10	70	4.25	8.67	0.71	0.5
Y19	The process addressed incomplete scope	5	10	70	2.69	3.30	0.38	0.14
Y20	The procurement approach promoted innovation and capacity building	6	10	70	2.64	6.13	0.5	0.25
Y21	The resulting design concept and consultant performance were satisfactory	5	10	70	72.02	72.02	3.01	9.06
Y22	The resulting project quality and contractor performance were satisfactory	23	10	70	7.47	11.27	0.76	0.56

5.3.3 Integrated model to predict the project performance outcomes based on A/E qualification and project characteristics (Model 5)

Time and cost performance

The construction cost and schedule indices and design schedule index were the output of the predicted model based on project characteristics and consultant qualifications. The list of qualifications and project characteristics correlated to each index are shown in Appendix A. The MAPE of the three models is below 23%. It could be observed that the MAPE of the indices as shown in Table 14 was lower compared to Model 3 and Model 4, which could indicate that project characteristics and consultant qualifications could mutually give an acceptable prediction for the indices. However, the design cost index was not accurately predicted using both elements (exceeded 100%); therefore, it was excluded.

Table 14. Cost and time models performances prediction performance (Model 5)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y2	Construction Cost Index (%)	6	80	20	11.19	22.5	1.03	1.06
Y3	Design Schedule Index (%)	13	10	40	6.08	18.84	1.95	3.84
Y4	Construction Schedule Index (%)	7	70	10	15.3	22.3	6.44	41.5

Adjustments, claims and compliance

The number of NCRs claims and RFIs was poorly associated to the ranking of the consultant qualifications and project characteristics with a MAPE of 47.41, 66.01, and 78.8, respectively. One possible explanation is that other variables could affect the number of claims and inquiries in a project such as the parties involved or other external factors. As for the other indicators, which are the number of change orders and the impact of claims and change orders on construction cost and time, the MAPE was below 35%, as shown in Table 15. This could indicate the significance of the correlation between the project characteristics and consultant qualifications on these indicators.

Table 15. Adjustments, claims and compliance prediction performance (Model 5)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y5	Number of Change Orders	18	80	40	20.5	32.97	43.5	1893.57
Y6	Impact of Change Orders on Construction Cost	9	80	40	11.8	19.05	0.64	0.41
Y7	Impact of Claims on Construction Cost	15	80	80	12.75	31.66	0.64	0.41
Y8	Number of Claims	5	10	70	7.06	78.85	8.32	69.28
Y9	Impact of Change Orders on Construction Schedule	20	10	70	0.8	18.54	0.6	0.36
Y10	Impact of Claims on Construction Schedule	13	20	70	7.3	8.19	0.58	0.33
Y11	Number of NCRs	8	10	70	31.08	47.41	22.39	501.65
Y12	Number of RFIs	13	10	80	26.99	66.01	85.86	7372.855

Time associated with procurement and owner's satisfaction

The MAPE for the procurement process time was about 35% for the variables as shown in Table 16. This could be indicative of the relationship between them and the project characteristics and consultant's qualifications.

As for owner satisfaction, it included the ranking of seven areas as shown in Table 16. Based on the dataset, six out of the seven satisfaction areas had a MAPE below 25%, which could indicate that project characteristics and the consultant qualifications could be predictive of owner satisfaction.

Table 16.Time associated with procurement and owner satisfaction prediction performance (Model 5)

Var. No.	Performance metrics	Input Layer (Nodes)	Hidden Layer 1	Hidden Layer 2	MPE (%)	MAPE (%)	RMSE	MSE
Y13	Time taken to select the consultant firm once a request for a bid has been made public	28	10	70	1.47	22.84	5.22	27.27
Y14	Time taken to approve the final design scope, plans, schedule, and fees	27	10	75	5.8	26.52	1.54	2.39
Y15	Time taken to award the selected consultant to execute the PSA	26	10	80	19.41	36.9	7.01	49.01
Y16	The procurement process ensured a competitive and cost-effective process	6	10	70	4.16	9.8	0.7	0.5
Y17	The selected procurement approach enhanced project effectiveness	11	15	20	0.26	19.34	0.81	0.65
Y18	The benefits of the procurement process outweighed associated risk	8	10	70	4.3	8.44	0.71	0.514
Y19	The process addressed incomplete scope	8	10	70	2.55	15.55	0.84	0.71
Y20	The procurement approach promoted innovation and capacity building	16	10	80	0.38	3.7	0.45	0.2
Y21	The resulting design concept and consultant performance were satisfactory	20	25	85	71.2	71.2	2.97	8.85
Y22	The resulting project quality and contractor performance were satisfactory	23	10	70	5.7	9.83	0.73	0.54

5.3.4 Proposed user interface

The proposed user interface for the tool under development is as shown in Figure 48. The user will be asked to upload the data sheet filled in a provided template then select the desired input either characteristics, qualifications, or both and finally the performance indicator. For example, if the user selected consultant qualifications and design schedule index, the model will work in the background to list the qualification correlated to the desired index and then the user will be asked to rank such qualifications and then the predicted indicator will be calculated as well as the errors.

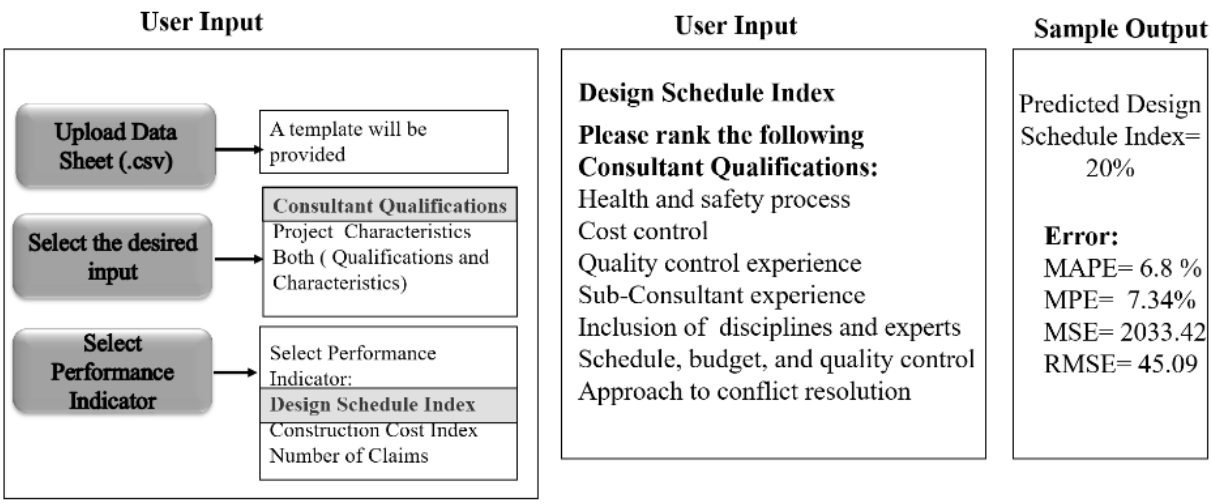

Figure 48. Proposed user interface

5.4 Face validation

Another verification and validation method as suggested by Sargent in 2007 includes face validation. In this method, individuals knowledgeable about the system were asked about the model performance, the inputs, and outputs of the model, and if model accurately represents the system. To achieve this, a panel of expert engineers were consulted. Consequently, the model performance, results, and process have been validated through their positive feedback on the performance of the model, the obtained results, and the logic in the conceptual model.

5.5 Summary

In this chapter, an ANN was to validate the output of the correlation analysis and to question the significance of consultant qualifications and project characteristics in predicting the project performance. The output of the correlation analysis was then used as the input for 22 prediction models for each of the performance indicators. Prior to training the prediction model, bootstrapping, which involves random resampling of the dataset to enhance the training capability of the prediction models, was implemented. The performance of the prediction models was calculated by comparing the actual value to the predicted values through the PE, MPE, MAPE, RMSE, and RSE. The output of the case study presented in Chapter 4 was validated. Three models were presented; all three share the same output, project performance indicators, with varying inputs. The first model input was the list of consultant qualifications; the second was the project characteristics; and the third model input was both. It was observed that including consultant qualifications as the input had better prediction performance compared to solely including the project characteristics. However, the integrated model (third model) had better prediction performance compared to the other two models, and this model could be used by owners to predict project performance based on project characteristics and consultant qualifications. A tool based on the proposed models is under development to aid owners in predicting quantified project performances based on the ranking of consultant qualifications and/or project characteristics. Such a tool will help owners to assess and predict the project outcomes during the procurement stage and aid and support their decision regarding consultant selection. The tool captures the variation of each project characteristics and the corresponding list of desirable consultant qualifications. Consequently, the owner will be able to determine the desirable qualifications and the impact of his compromise/if any on the project outcomes. This tool will help to set back the industry practices of having unstandardized evaluation criteria to assess consultants and connects the gap between the consultant procurement decision and management performance of a project.

In conclusion, the association and correlations between the consultant qualifications and project outcomes were confirmed and validated. Therefore, as the consultant qualifications get stronger in some areas, as listed in Appendix B, the associated performance indicator will be better. This urges the need of selecting consultants based on their technical qualifications to enhance project performances.

CHAPTER 6. SUMMARY, LIMITATION AND FUTURE WORK

6.1 Research Summary

6.1.1 Identify the current procurement practices adopted by big and medium sized cities in Alberta to select A/E consultant

This thesis is mainly concerned with the selection of A/E consultants. In this context, structured interviews were conducted with 11 Alberta-based municipalities, and it was observed that most adopt the lowest-price bid procurement approach for small-scale standard projects. For large, scaled projects, 9% of the interviewed sample adopted QBS, while the rest used BVP through one envelope or two envelope submission. BVP combines qualifications and cost, but one of its major disadvantages is that the owners tend to give the same score for qualifications. Thus, the fee is the determining factor, which could sacrifice project performance.

Considering this, the interviewed participants were then asked to share their perceptions and experiences regarding the potential benefits and challenges of QBS implementation within their organizations. 23% agreed that QBS can provide a clearer scope definition because of joint discussions and scope development between clients and consultants. They also agreed the fee estimation that takes place during the negotiation stage will be more accurate and subject to fewer changes compared to other methods. Moreover, 8% of participants agreed that QBS provides long-term benefits such as life cycle cost savings. On the other hand, 8% expressed their concerns when selected A/E firms change their team members after the selection process. Also, 23% of participants believe that the qualitative nature of evaluating qualifications under QBS is a drawback hindering its wider adoption. 24% of participants stated that excluding the fee from the proposal would lead to over pricing of the proposal, and 38% opted out from sharing their opinion regarding the matter. Based on the interviews, 91% of the interviewed sample combines fee with qualifications.

6.1.2 Identifying criteria used for evaluating A/E qualifications during the selection process

To identify the common evaluation criteria for assessing A/E consultants, a set of 94 RFP documents were collected and analyzed. The analysis revealed seven commonly used A/E evaluation criteria among several Alberta-based public owners: project comprehension and methodology, team composition and experience, financial score, firm's experience and qualifications, past performance, time, schedule project control, and innovation and value added.

The respective average weights of the criteria vary between 9% and 26%. The maximum and minimum weight for each evaluation criterion showed huge variability, which indicates a lack of a standardized evaluation criteria across the sample. For example, the minimum weight for "project comprehension and methodology" was 10%, and the maximum weight was 60%.

Project characteristics were analyzed against evaluation criteria to identify any changes in occurrence and weighting of criteria. These variations are compared across the two common project types, land development and roads. The difference in weights and occurrence frequency of criteria between the two types of projects indicated that project type can impact what criteria are used by owners to evaluate A/E firms.

6.1.3 Define and evaluate the most important A/E qualifications and project characteristics that affect and predict project outcomes

A questionnaire was administered to define which A/E qualifications affect project outcomes and collect project data. Part A of the questionnaire was answered by procurement team and captured the ranking of A/E qualifications and project characteristics. Part B was addressed to the management team and collect the performance outcomes of the projects. A case study of 18 projects were solicited and analyzed to compare when price was and was not a selection criterion for A/E consultants. Projects where price was not included outperformed the priced based approaches. QBS projects were linked to better schedule and cost performance during design and construction of projects. Also, QBS projects were associated with lower adjustments and changes to the budgeted cost and time, as well as shorter procurement time.

A correlation analysis model was developed using Spearman and Kendall correlation coefficients and was then used to study the relationship among consultant qualifications, project characteristics, and the project performance outcomes. Consultant qualifications and project characteristics that were correlated to the project performance indicators were then identified based on the significance of the correlation coefficient. These performance indicators included design schedule index, construction schedule index, design schedule index, construction schedule index, number of change orders, impact of change orders on construction cost and time, impact of claims of construction cost and time, number of NCRs and RFIs, owner satisfaction, and the time associated with the procurement process. Based on the case study findings, various consultant qualifications and project characteristics were significantly correlated to the performance of the projects. For example, design schedule index was correlated to thirteen variables; seven of which are consultant qualifications, and the rest are project characteristics. The correlated consultant qualifications are healthy and safety processes, cost control, quality control experience, sub-consultant experience, inclusion of necessary disciplines and experts, approach to schedule, budget and project control, and approach to conflict resolution. As for the project characterises correlated to design schedule index, they include the risk of working with the consultant, technical complexity of the design, cost complexity, number of firms collaborating, interdependencies of the trades and tasks, and the type of consultant firm selection (from a prequalified list or selected through an open bid). The list of consultant qualifications and project characteristics correlated to each of the performance indicators are shown in Appendix B.

To verify the list of variables obtained from the correlation analysis, a prediction model was developed. Bootstrapping was used to improve the training performance of the prediction model. An ANN was applied to verify the output of the correlation analysis and to question the significance of consultant qualifications in predicting the project performance. The performance indicators covered six areas: time, cost, change orders and adjustments, compliance and inquiries, time associated with the procurement process, and owner's satisfaction. The output of the correlation analysis was then used as the input variables for 22 prediction models. The performance of the prediction models was calculated by comparing the actual value to the predicted values by calculating the PE, MPE, MAPE, RMSE, and RSE. Based on the case study findings, the MAPE of 14 out of the 22 models was below 35%, which indicates good prediction performance and demonstrates the significance of the correlation between the consultant's qualifications and the project performance indicators. Figure 49 illustrates the input and output process of one of the performance indicators which is design schedule index. The A/E qualifications shown in the figure are the output of the correlation analysis, which were then used as an input to the prediction model.

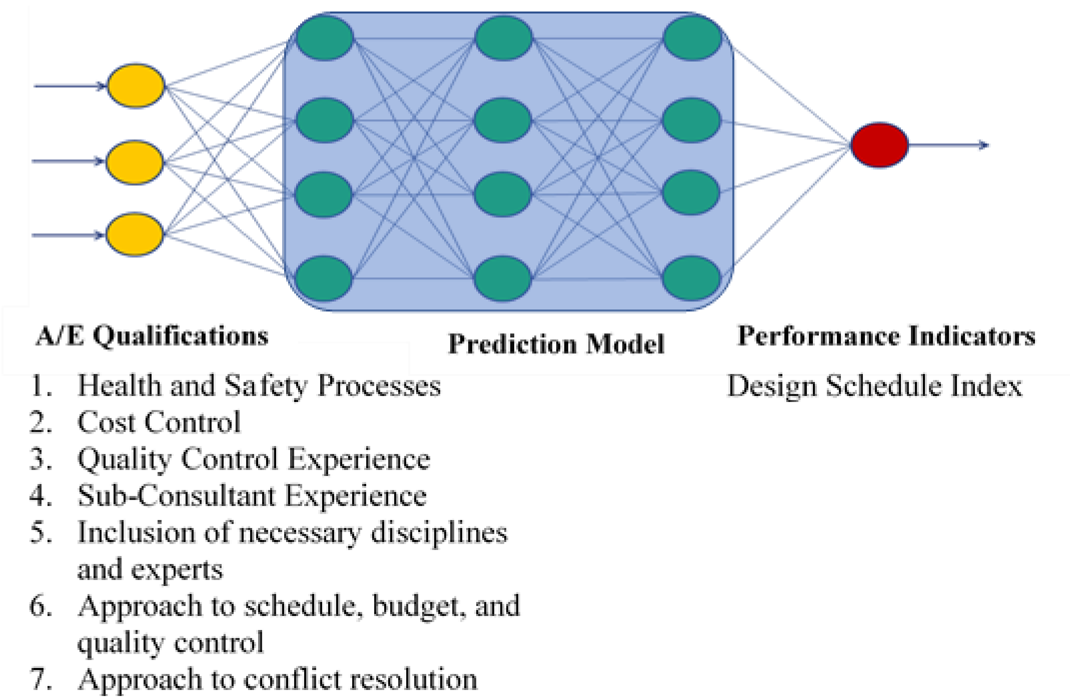

Figure 49. Example of prediction model process

Five models were developed, as shown in Figure 50. The first stage involved developing the correlation analysis models. The inputs for correlation Model 1 were consultant qualifications, and the output was list of qualifications that are correlated to each of the performance indicators. Model 2 included project characteristics as the sole input. Once the list of A/E consultant qualifications and project characteristics in relation to the performance indicators were obtained; they were the input to the validation models. Validation Model #3 input was the correlated consultant qualifications; validation Model 4 input was the correlated project characteristics; and validation Model 5 combined both. The purpose of segregating the inputs was to avoid any noise other variables might cause and to question the impact that each variable has on project performance. In Model 5, both variables were combined to make the model more realistic, as project characteristics are an inherent feature in any project.

This thesis presents the first attempt to evaluate QBS execution quantitatively and subjectively in Alberta to understand the effects of A/E capabilities on venture performance. This study used quantitative-based data rather than anecdotal evidence. Public associations can then assess and comprehend the impacts of procurement methods, project characteristics, and which A/E qualification impact project outcomes. To summarize, this study confirms correlations between consultant qualifications and project performance. Higher ranking of A/E consultant qualification in certain areas is associated with better project performance.

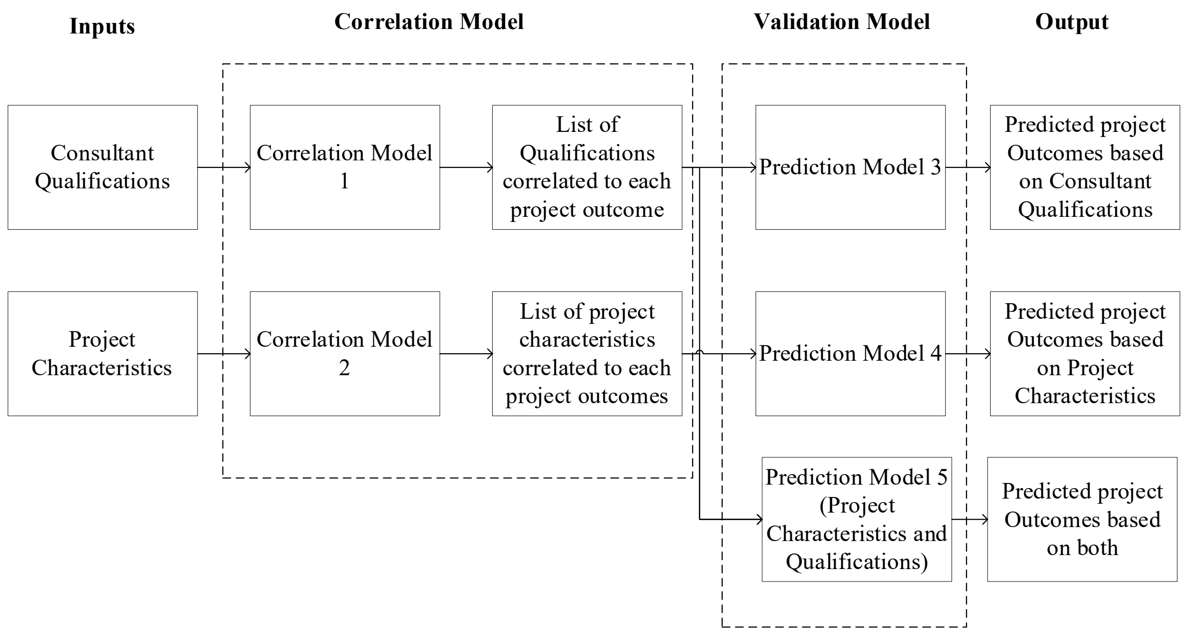

Figure 50. Model process summary

6.2 Limitations and challenges

One of the main challenges of this research was the data collection process. Initially, 14 public owners were asked to share the required project data. However, this approach was deemed unsuccessful due to the lack of a central share point where procurement project data and management and performance outcomes were stored. Also, the sampling approach used was volunteer sampling; therefore, rejection of participation impacted the sample representation.

A questionnaire was administered which was divided into two parts (procurement related data and management data) as a work around for the lack of a central share point. However, the current pandemic and economic crisis have had a huge impact of the response rate and the participation of the owners. This situation resulted in a significant reduction in expected responses, project population size, and diversity in the sample, which limits the robustness of the statistical results.

To be able to generalize the findings of the questionnaire responses, a larger population size is required.

QBS is not a popular procurement method in Alberta. More QBS project samples are needed to compare against the higher number of non-QBS projects provided by the public firms. Thus, the results of the obtained sample are presented as a case study finding to implement the suggested models. The tool under development can be used upon the availability of more responses. It should be noted that further responses could improve or impair the performance of the project.

6.3 Recommendations and future work

This study has indicated an association between A/E consultant qualification and project performance indicators. Also, it was observed that QBS projects tend to have more favorable project performance in comparison to methods where price is an evaluation criterion. These findings are supported by results from different studies conducted in other Canadian regions and the US. Therefore, the efforts towards adopting QBS should be ongoing to deliver more value and enhanced project performances.

This study developed data acquisition model for capturing important consultant qualifications and project outcomes in the future. As more data is collected over time, the project population size will be increased. At that point, the findings should be revisited and analyzed considering the new statistical results. A sample size between 33–40 would be desirable given sample sizes used in similar studies. This thesis delivers the first stage of a two-stage research project. The second stage will be extended towards developing a decision-support tool, which can be used by various organizations, to fairly and transparently allocate the most qualified A/E services provider to each project during procurement decisions.

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APPENDIX A: Survey to Public Owners

PART A: Management

This section will focus on project characteristics and management performance to better understand the associations between A/E qualifications and project outcomes.

SECTION 1: Project Characteristics

1. Demographics

a. Project Type and Location

- ☐ Commercial
- ☐ Industrial
- ☐ Transportation
- ☐ Land Development
- ☐ Water/Environmental
- ☐ Institutional (e.g., government, hospital, school)

  Location (City): ____________________________

b. Design Procurement Method:

- ☐ QBS: *quality is the determining factor; fee is not a factor in the evaluation*
- ☐ QCBS: *major weight is on quality (e.g., >50%); fee has a lower weight*
- ☐ Best Value One-Envelope: *fee in same envelope*
- ☐ Best Value Two-Envelopes: *fee in separate envelope*
- ☐ Low-Bid: *lowest bid is the determining factor*
- ☐ Sole Source: *selection without a competitive process*
- ☐ Other: ____________________________________

c. Construction Delivery Method:

- ☐ Design-Bid-Build
- ☐ Design-Build
- ☐ Construction Management
- ☐ Other: ____________________________________

d. A/E Consultant Firm Selected to Bid:

- ☐ From an existing list of pre-qualified firms
- ☐ Through an open bidding process
- ☐ Other: ____________________________________

e. Project Completion Phase:

- ☐ Design and construction phases completed
- ☐ Only design phase completed; construction phase has not begun or is in progress
- ☐ Design phase partially completed;

  Please specify completed design phases: ___________________________________

2. Project Risks

Please rate the associated project risks for each factor (*1 = Low, 5 = High)*:

a. Completing project on time and on budget	1	2	3	4	5
b. Community requiring changes to the proposed design (i.e., social risk)	1	2	3	4	5
c. Political officials requiring changes to the proposed design (i.e., political risk)	1	2	3	4	5
d. Risk of working with consultant firm (i.e., qualifications, knowledge, etc.)	1	2	3	4	5

3. Design and Project Complexity

Please rate the level of design and project complexity for each factor (*1 = Low, 5 = High*):

a. Technical complexity (i.e., complexity of technical requirements within one specialty and/or number of technical specialties required)	1	2	3	4	5
b. Performance requirements	1	2	3	4	5
c. Location-based complexities	1	2	3	4	5
d. Project cost-related complexities	1	2	3	4	5
e. Number of firms collaborating	1	2	3	4	5
f. Interdependencies of construction trades and tasks	1	2	3	4	5

4. Social Factors

Please rate the extent to which the consultant addressed these factors in their design (*1 = Did Not Address, 5 = Addressed Completely)*:

a. Sustainability aspects	1	2	3	4	5
b. Community impact	1	2	3	4	5
c. Human factors for employees in the infrastructure or facility	1	2	3	4	5
d. Human factors for end users of the infrastructure or facility	1	2	3	4	5

SECTION 2: Project Performance and Outcomes

1. Cost and Schedule Performance

Please answer the following questions regarding the cost and schedule performance of the project. For projects not yet completed, please answer for the **completed phases** only.

a. What was the predicted (i.e., budgeted) *design fee* amount or range (in CAD)?	
b. What was the actual (i.e., final) *design fee* amount or range (in CAD)?	
c. What was the planned *design* schedule (in weeks)?	
d. What was the actual *design* schedule (in weeks)?	
e. What was the predicted (i.e., budgeted) *construction cost* or range (in CAD)?	
f. What was the actual (i.e., final) *construction cost* or range (in CAD)?	
g. What was the planned *construction* schedule (in weeks)?	
h. What was the actual *construction* schedule (in weeks)?	

2. Changes to Project

Please answer the following questions regarding the cost and schedule performance of the project *(1 = Low, 5 = High)*:

a.	How many design and construction change orders were issued during the project?	Number/ Range:				
b.	What was the impact of change orders on construction cost?	1	2	3	4	5
c.	Please indicate the impact on cost in CAD or as a %:	Cost:				
d.	What was the impact of change orders on the construction schedule?	1	2	3	4	5
e.	Please indicate the impact on schedule in weeks or as a %:	Time:				
f.	How many RFIs, approximately, were issued?	Number/ Range:				
g.	How many NCRs, approximately, were issued?	Number/ Range:				
h.	How many claims (all types), approximately, were submitted?	Number/ Range:				
i.	What was the impact of claims on construction cost?	1	2	3	4	5
	Please indicate the impact on cost in CAD or as a %:	Value:				
j.	What was the impact of claims on the construction schedule?	1	2	3	4	5
	Please indicate the impact on schedule in weeks or as a %:	Time:				

3. Overall Satisfaction with Procurement Process and Project Outcomes

From a managerial perspective, please specify your level of agreement with the statements below *(1 = Strongly Disagree, 5 = Strongly Agree)*:

a.	The procurement process ensured a competitive and cost-effective process	1	2	3	4	5
b.	The selected procurement approach enhanced project effectiveness	1	2	3	4	5
c.	The benefits of the procurement process outweighed associated risks	1	2	3	4	5
d.	The process addressed incomplete scope	1	2	3	4	5
e.	The procurement approach promoted innovation and capacity building	1	2	3	4	5
f.	The resulting design concept and consultant performance was satisfactory	1	2	3	4	5
g.	The resulting project quality and contractor performance was satisfactory	1	2	3	4	5

PART B: Procurement

This section will focus on the qualifications of the A/E firm and the *procurement* process to better understand the associations between A/E qualifications and project outcomes.

SECTION 1: Consultant Firm Qualifications Evaluation During Procurement

1. Firm Qualifications and Experience

Please rate the consultant firm's level of expertise in each area *(1 = Poor, 3 = Average, 5 = Excellent):*

a.	Project management	1	2	3	4	5
b.	Quality control	1	2	3	4	5
c.	Health and safety processes	1	2	3	4	5
d.	Cost control	1	2	3	4	5
e.	Sub-consultant experience and working relationships	1	2	3	4	5
f.	Environmental policies	1	2	3	4	5

2. Project Team Composition and Qualifications

Please rate the project team's qualifications in each area *(1 = Poor, 3 = Average, 5 = Excellent)*:

a.	Identification of key personnel's roles and responsibilities	1	2	3	4	5
b.	Years of experience of key personnel	1	2	3	4	5
c.	Professional accreditation	1	2	3	4	5
d.	Assignment of resources	1	2	3	4	5
e.	Inclusion of necessary disciplines and experts	1	2	3	4	5

3. Project Comprehension and Methodology

Please rate the firm's performance in each area *(1 = Poor, 3= Average, 5 = Excellent)*:

a.	Understanding of desired project outcomes	1	2	3	4	5
b.	Appropriate project description and addressing of pertinent issues	1	2	3	4	5
c.	Clear indication of included, excluded, optional, and outsourced services	1	2	3	4	5
d.	Identification of deliverables for each task or phase	1	2	3	4	5
e.	Approach to schedule, budget, and quality control	1	2	3	4	5
f.	Approach to conflict resolution	1	2	3	4	5
g.	Design innovation and value engineering	1	2	3	4	5

4. Relevant Project Experience and Past Performance

Please rate the firm's performance in each area *(1 = Poor, 3 = Average, 5 = Excellent)*:

a.	Firm designed projects of similar nature and scope	1	2	3	4	5
b.	Demonstration of local knowledge	1	2	3	4	5
c.	Relevant project awards	1	2	3	4	5
d.	Strength of references from clients of relevant projects	1	2	3	4	5
e.	Scope of services rendered, constraints, and deliverables of relevant projects provided	1	2	3	4	5

SECTION 2: Owner-Consultant Relationship

1. Owner/Consultant Involvement

a. How many projects, approximately, has your organization awarded the consultant firm in the last 10 years?

- ☐ Less than 5
- ☐ 5 to 10
- ☐ More than 10

b. What percentage, approximately, of your organization's projects has the consultant firm been procured for?

____

c. How many years, approximately, have you been working with the consultant firm?

____

d. Please specify your level of agreement *(1 = Strongly Agree, 5 = Strongly Disagree)*:

i.	Your organization and the consultant firm's personnel interact frequently	1	2	3	4	5
ii.	The majority of interactions between your organization and the consultant firm are productive and yield positive outcomes	1	2	3	4	5
iii.	Compared to other firms that you have worked with, the consultant firm is trustworthy	1	2	3	4	5
iv.	Your overall experience working with the consultant firm has been positive	1	2	3	4	5
v.	You can rely on the consultant firm to commit to their promised plan	1	2	3	4	5
vi.	Throughout the procurement process, the amount and type of administrative procedures between your firm and the consultant's firm were reasonable	1	2	3	4	5

SECTION 2: Procurement Process of Consultant

1. Time Associated with Procurement Process

Please provide an approximate range (in weeks) of the time required to:

1. Select a consultant firm once a request for a bid had been made public: ____________________
2. Approve the final design scope, plans, schedules, and fees: ____________________
3. Award the selected consultant firm to execute the PSA: ____________________

2. Overall Satisfaction with Procurement Process and Project Outcomes

From a procurement perspective, please specify your level of agreement with the statements below *(1 = Strongly Disagree, 5 = Strongly Agree)*:

a.	The procurement process ensured a competitive and cost-effective process	1	2	3	4	5
b.	The selected procurement approach enhanced project effectiveness	1	2	3	4	5
c.	The benefits of the procurement process outweighed associated risks	1	2	3	4	5
d.	The process addressed incomplete scope	1	2	3	4	5
e.	The procurement approach promoted innovation and capacity building	1	2	3	4	5
f.	The resulting design concept and consultant performance was satisfactory	1	2	3	4	5
g.	The resulting project quality and contractor performance was satisfactory	1	2	3	4	5

APPENDIX B: Correlations between Variables

Table A. Performance indicators (dependent variables)

No.	Performance Indicators	Description
		Cost
Y1	Design Cost Index (%)	[(Actual Design Fee - Budgeted Design Fee)/ Budgeted Design Fee] *100
Y2	Construction Cost Index (%)	[(Actual Construction Cost - Budgeted Construction Cost)/ Budgeted Construction Cost] *100
		Time
Y3	Design Schedule Index (%)	[(Actual Design Time - Budgeted Design Time)/ Budgeted Design Time] *100
Y4	Construction Schedule Index (%)	[(Actual Construction Time - Budgeted Construction Time)/ Budgeted Construction Time] *100
		Adjustments and Changes
Y5	Number of Change Orders	Numerical input defined by participant (open ended)
Y6	Impact of Change Orders on Construction Cost	In percentage (%) = [Impact of Change Orders on Construction Cost (CAD) / Actual Construction Cost (CAD)] * 100 Ordinal scale 1-5, 1=very low, 5=Very High
Y7	Impact of Claims on Construction Cost	In percentage (%) = [Impact of Claims on Construction Cost (CAD) / Actual Construction Cost (CAD)] * 100 Ordinal scale 1-5, 1=very low, 5=Very High
Y8		Numerical input defined by participant
Y9	Impact of Change Orders on Construction Time	In percentage (%) = [Impact of Change Orders on Construction Time (Weeks) / Actual Construction Time (Weeks)] * 100 Ordinal scale 1-5, 1=very low, 5=Very High
Y10	Impact of Claims on Construction Time	In percentage (%) = [Impact of Claims on Construction Time (Weeks) / Actual Construction Time (Weeks)] * 100 Ordinal scale 1-5, 1=very low, 5=Very High
		Compliance and Inquiries
Y11	Number of NCRs	Numerical input defined by participant (open ended)
Y12	Number of RFIs	Numerical input defined by participant (open ended)
		Time associated with Procurement Process
Y13	Time taken to select the consultant firm once a request for a bid has been made public	Time in weeks (open ended)
Y14	Time taken to approve the final design scope, plans, schedule, and fees	Time in weeks (open ended)

No.	Performance Indicators	Description
Y15	Time taken to award the selected consultant to execute the PSA	Time in weeks (open ended)
		Owner Satisfaction
Y16	The procurement process ensured a competitive and cost-effective process	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y17	The selected procurement approach enhanced project effectiveness	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y18	The benefits of the procurement process outweighed associated risk	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y19	The process addressed incomplete scope	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y20	The procurement approach promoted innovation and capacity building	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y21	The resulting design concept and consultant performance were satisfactory	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree
Y22	The resulting project quality and contractor performance were satisfactory	Ordinal scale 1-5, 1=Strongly Disagree, 5=Strongly Agree

Table B. Factors that may affect project performance (independent variables)

Var. no.	Independent Variables	Description
		Project Characteristics
X1	Project Type	1= Transportation, 2= Institutional,3=Residential,4=Water/Environmental,5=Neighbourhood Rehabilitation,5= Housing and Commercial
X2	Design Procurement Method	1= Non-QBS,2= QBS
X3	Consultant Firm Selection	1= Prequalified list, 2= Open Bid, 3= Competition
X4	Construction Delivery Method	1= CM, 2= DBB, 3= DB, 4=PM
		Project Risks

Var. no.	Independent Variables	Description
X5	Completing project on budget and time	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X6	Community requiring changes to the proposed design (Social Risk)	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X7	Political Officials requiring changes to the proposed design (Political Risk)	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X8	Risk of working with consultant firm (i.e., qualifications, knowledge, etc.)	Scale 1-5 or N/A, 1= Very Low, 5= Very High
		Design and Project Complexity
X9	Technical Complexity	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X10	Performance requirements	Scale 1-5 or N/A, 1= Very Low, 5= Very High Scale 1-5 or N/A, 1= Very Low, 5= Very High
X11	Location-based complexities	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X12	Project cost related complexities	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X13	Number of firms collaborating	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X14	Interdependencies of construction trades and tasks	Scale 1-5 or N/A, 1= Very Low, 5= Very High
		Social Factors
X15	Sustainability aspects	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X16	Community Impact	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X17	Human Factors for employees during construction process	Scale 1-5 or N/A, 1= Very Low, 5= Very High
X18	Human factors for end users	Scale 1-5 or N/A, 1= Very Low, 5= Very High
		Consultant's Qualifications
	Firm Qualifications and Expertise	
X19	Project Management	Ordinal scale 1-5, 1=Poor, 5=Excellent
X20	Quality Control	Ordinal scale 1-5, 1=Poor, 5=Excellent
X21	Health and Safety processes	Ordinal scale 1-5, 1=Poor, 5=Excellent
X22	Cost Control	Ordinal scale 1-5, 1=Poor, 5=Excellent
X23	Sub-consultant experience and working relationships	Ordinal scale 1-5, 1=Poor, 5=Excellent
X24	Environmental Policies	Ordinal scale 1-5, 1=Poor, 5=Excellent
	Project Team Composition and Qualifications	
X25	Identification of key personnel's roles and responsibilities	Ordinal scale 1-5, 1=Poor, 5=Excellent
X26	Years of experience of key personnel	Ordinal scale 1-5, 1=Poor, 5=Excellent
X27	Professional accreditation	Ordinal scale 1-5, 1=Poor, 5=Excellent
X28	Assignment of resources	Ordinal scale 1-5, 1=Poor, 5=Excellent
X29	Inclusion of necessary disciples and experts	Ordinal scale 1-5, 1=Poor, 5=Excellent
	Project Comprehension and Methodology	
X30	Understanding of desired project outcomes	Ordinal scale 1-5, 1=Poor, 5=Excellent
X31	Appropriate project description and addressing of pertinent issues	Ordinal scale 1-5, 1=Poor, 5=Excellent
X32	Clear indication of included, excluded, optional, and outsourced services	Ordinal scale 1-5, 1=Poor, 5=Excellent
X33	Identification of deliverables for each task or phase	Ordinal scale 1-5, 1=Poor, 5=Excellent
X34	Approach to schedule, budget, and quality control	Ordinal scale 1-5, 1=Poor, 5=Excellent
X35	Approach to conflict resolution	Ordinal scale 1-5, 1=Poor, 5=Excellent
X36	Design innovation and value engineering	Ordinal scale 1-5, 1=Poor, 5=Excellent

Var. no.	Independent Variables	Description
	Relevant Project Experience and Past performance	
X37	Experience designing projects of similar nature and scope	Ordinal scale 1-5, 1=Poor, 5=Excellent
X38	Demonstration of local knowledge	Ordinal scale 1-5, 1=Poor, 5=Excellent
X39	Receipt of relevant project awards	Ordinal scale 1-5, 1=Poor, 5=Excellent
X40	Strength of references from clients of relevant projects	Ordinal scale 1-5, 1=Poor, 5=Excellent
X41	Scope of services rendered, constraints, and deliverables of relevant projects	Ordinal scale 1-5, 1=Poor, 5=Excellent
		Owner- Consultant Relationship
X42	Percentage of projects owner firm procured to the consultant (%)	Numerical percentage defined by the user (open ended)
X43	Number of years owner and consultant worked together	Numerical input defined by the user (open ended)
	Previous Interactions	
X44	Your organization and the consultant firm interact frequently	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree
X45	The majority of interactions between the organization and the consultant firm are productive and yield positive outcomes	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree
X46	Compared to other firms, the consultant firm is trustworthy	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree
X47	Your overall experience working with the consultant firm has been positive	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree
X48	You can rely on the consultant firm to commit to their promised plan	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree
X49	Throughout the procurement process the amount and type of admin. procedures were reasonable	Scale 1-5, 1= Strongly Disagree, 5= Strongly Agree

Table C. Correlations between A/E qualifications and project performance

Description	Correlation Coefficient
Y1: Design Cost Index	
Identification of Key Personnel’s roles and responsibilities	-0.43
Project Management Experience	-0.37
Design Innovation and Value Engineering	-0.37
Y2: Construction Cost Index	
Cost Control	-0.4
Health and Safety Processes	-0.26
Strength of references from clients of relevant projects	-0.41
Y3: Design Schedule Index	
Health and Safety Processes	-0.43
Cost Control	-0.31
Quality Control Experience	-0.31
Sub-Consultant Experience	-0.29
Inclusion of necessary disciplines and experts	-0.54

Description	Correlation Coefficient
Approach to schedule, budget, and quality control	-0.48
Approach to conflict resolution	-0.32
Y4: Construction Schedule Index	
Cost Control	-0.41
Sub-Consultant Experience	-0.35
Appropriate project description and addressing of pertinent issues	-0.29
Approach to schedule, budget, and quality control	-0.35
Y5: Number of Change Orders	
Project Management Experience	-0.42
Environmental Policies	-0.36
Quality Control Experience	-0.29
Inclusion of necessary disciplines and experts	-0.31
Understanding of desired project outcomes	-0.35
Appropriate project description and addressing of pertinent issues	-0.4
Clear indication of included and excluded services	-0.49
Identification of deliverables for each task and phase	-0.38
Experience designing projects of similar nature and scope	-0.33
Scope of services rendered, constraints, and deliverables of relevant projects	-0.49
Y6: Impact of Change Orders on Construction Cost (ordinal)	
Environmental Policies	-0.36
Project Management Experience	-0.35
Inclusion of necessary disciplines and experts	-0.36
Understanding of desired project outcomes	-0.34
Clear indication of included and excluded services	-0.43
Design Innovation and Value Engineering	-0.33
Strength of references from clients of relevant projects	-0.37
Y7: Impact of Claims on Construction Cost	
Project Management Experience	-0.31
Quality Control Experience	-0.38
Sub-consultant experience	-0.52
Years of experience of key personnel	-0.38
Understanding desired project outcomes	-0.66
Appropriate project description and addressing of pertinent issues	-0.55
Clear indication of included, excluded, optional, and outsourced services	-0.35
Identification of deliverables for each task or phase	-0.45
Design Innovation and Value Engineering	-0.34
Scope of services rendered, constraints, and deliverables of relevant projects	-0.52
Y8: Number of Claims	
Health and Safety Processes	-0.3
Approach to schedule, budget, and control	-0.37
Experience designing projects of similar nature and scope	-0.36
Y9: Impact of Change Orders on Construction Time	
Project Management Experience	-0.35
Health and Safety Processes	-0.31
Cost Control	-0.52
Sub-Consultant Experience	-0.58
Environmental Policies	-0.35

Description	Correlation Coefficient
Assignment of Resources	-0.51
Years of Experience of key personnel	-0.39
Professional accreditation	-0.39
Assignment of resources	-0.51
Inclusion of necessary disciplines and experts	-0.35
Understanding of desired project outcomes	-0.46
Appropriate project description and understanding pertinent issues	-0.64
Identification of deliverables for each task or phase	-0.53
Approach to schedule, budget, and quality control	-0.78
Approach to conflict resolution	-0.66
Experience designing project of similar nature and scope	-0.41
Strength of References from clients of relevant projects	-0.5
Scope of services rendered, constraints, and deliverables of relevant projects	-0.36
Y10: Impact of Claims on Construction Time	
Cost Control	-0.37
Sub-consultant Experience	-0.52
Understanding of desired project outcomes	-0.45
Appropriate project description and addressing of pertinent issues	-0.62
Identification of deliverables for each task or phase	-0.42
Approach to schedule, budget, and quality control	-0.43
Scope of services rendered constraints and deliverables of relevant projects	-0.39
Strength of references from clients of relevant projects	-0.35
Y11: Number of NCRs	
Assignment of Resources	-0.42
Approach to schedule, budget, and control	-0.32
Y12: Number of RFIS	
Environmental Policies	-0.31
Experience designing projects of similar nature and scope	-0.38
Scope of services rendered, constraints, and deliverables of relevant projects	-0.34
Y13: Time taken to select the consultant firm once a request for a bid has been made public	
Project Management Experience	0.42
Quality Control Experience	0.48
Health and Safety Processes	0.64
Cost Control	0.45
Sub-consultant Experience	0.48
Environmental Policies	0.45
Identification of key personnel's roles and responsibilities	0.52
Years of experience of key personnel	0.51
Professional accreditation	0.42
Assignment of resources	0.57
Inclusion of necessary disciples and experts	0.42
Understanding of desired project outcomes	0.39
Appropriate project description and addressing of pertinent issues	0.45
Clear indication of included, excluded, optional, and outsourced services	0.48
Identification of deliverables for each task or phase	0.52
Approach to schedule, budget, and quality control	0.43
Approach to conflict resolution	0.67
Design innovation and value engineering	0.5
Experience designing projects of similar nature and scope	0.3
Demonstration of local knowledge	0.4

Description	Correlation Coefficient
Receipt of relevant project awards	0.42
Strength of references from clients of relevant projects	0.53
Scope of services rendered, constraints, and deliverables of relevant projects	0.37
Y14: Time taken to approve the final design scope, plans, schedule, and fees	
Project Management Experience	0.36
Quality Control Experience	0.34
Health and Safety Processes	0.52
Cost Control	0.5
Sub-consultant Experience	0.39
Environmental Policies	0.39
Identification of key personnel's roles and responsibilities	0.38
Years of experience of key personnel	0.4
Professional accreditation	0.59
Assignment of resources	0.46
Inclusion of necessary disciples and experts	0.39
Understanding of desired project outcomes	0.21
Appropriate project description and addressing of pertinent issues	0.28
Clear indication of included, excluded, optional, and outsourced services	0.21
Identification of deliverables for each task or phase	0.3
Approach to schedule, budget, and quality control	0.62
Approach to conflict resolution	0.59
Design innovation and value engineering	0.41
Experience designing projects of similar nature and scope	0.43
Demonstration of local knowledge	0.54
Receipt of relevant project awards	0.49
Strength of references from clients of relevant projects	0.48
Scope of services rendered, constraints, and deliverables of relevant projects	0.3
Y15: Time taken to award the selected consultant to execute the PSA	
Project Management Experience	0.5
Quality Control Experience	0.6
Health and Safety Processes	0.33
Cost Control	0.49
Sub-consultant Experience	0.52
Environmental Policies	0.45
Identification of key personnel's roles and responsibilities	0.42
Years of experience of key personnel	0.52
Professional accreditation	0.7
Assignment of resources	0.49
Inclusion of necessary disciples and experts	0.51
Understanding of desired project outcomes	0.44
Appropriate project description and addressing of pertinent issues	0.46
Clear indication of included, excluded, optional, and outsourced services	0.37
Identification of deliverables for each task or phase	0.44
Approach to schedule, budget, and quality control	0.63
Approach to conflict resolution	0.48
Design innovation and value engineering	0.51
Experience designing projects of similar nature and scope	0.42
Demonstration of local knowledge	0.48
Receipt of relevant project awards	0.51
Strength of references from clients of relevant projects	0.56
Scope of services rendered, constraints, and deliverables of relevant projects	0.57

Description	Correlation Coefficient
Y16: The procurement process ensured a competitive and cost-effective process	
Design innovation and value engineering	0.32
Y17: The selected procurement approach enhanced project effectiveness	
Sub-consultant experience	0.46
Understanding of desired project outcomes	0.56
Appropriate project description and addressing pertinent issues	0.55
Identification of deliverables for each task or phase	0.42
Design Innovation and value engineering	0.39
Demonstration of local knowledge	0.3
Scope of services rendered constraints and deliverables of relevant projects	0.32
Y18: The benefits of the procurement process outweighed associated risk	
Sub-consultant experience	0.42
Appropriate project description and addressing pertinent issues	0.57
Identification of deliverables for each task or phase	0.32
Design Innovation and value engineering	0.3
Y19: The process addressed incomplete scope	
Appropriate project description and addressing pertinent issues	0.33
Understanding of desired project outcomes	0.42
Design innovation and value engineering	0.33
Y20: The resulting design concept and consultant performance were satisfactory	
Appropriate project description and addressing pertinent issues	0.49
Project management experience	0.5
Quality control experience	0.41
Environmental policies	0.34
Identification of personnel roles and responsibilities	0.5
Assignment of resources	0.39
Inclusion of necessary disciplines and experts	0.34
Understanding of desired project outcomes	0.44
Clear indication of included and excluded services	0.66
Identification of deliverables for each task or phase	0.46
Design Innovation and Value Engineering	0.54
Receipt of relevant project awards	0.34
Y21: The resulting project quality and contractor performance were satisfactory	
Appropriate project description and addressing pertinent issues	0.5
Project Management experience	0.65
Identification of key personnel's roles and responsibilities	0.57
Years of experience of key personnel	0.54
Professional accreditation	0.62
Assignment of resources	0.55
Inclusion of necessary disciplines and experts	0.37
Understanding of desired project outcomes	0.59
Clear indication of included and excluded services	0.47
Identification of deliverables for each task or phase	0.56
Approach to schedule, budget, and control	0.4
Approach to conflict resolution	0.7
Design innovation and value engineering	0.72
Demonstration of local knowledge	0.67
Experience designing projects of similar nature and scope	0.32
Receipt of relevant project awards	0.51
Strength of references from clients of relevant projects	0.37

Description	Correlation Coefficient
Y22: The procurement approach promoted innovation and capacity building	
Appropriate project description and addressing pertinent issues	0.46
Project management experience	0.34
Sub-consultant experience	0.39
Identification of key personnel's roles and responsibilities	0.43
Assignment of resources	0.39
Understanding of desired project outcomes	0.49
Identification of deliverables for each task or phase	0.4
Approach to schedule, budget, and control	0.46
Approach to conflict resolution	0.5
Design innovation and value engineering	0.48

Table D. Correlations between Project Characteristics and project performance

Description	Correlation Coefficient
Y1: Design Cost Index (%)	
Risk with working with the consultant firm	0.38
Technical Complexity	-0.3
Interdependencies of construction trades and tasks	-0.32
Sustainability Aspects	-0.35
Human Factor for Employees during the construction process	-0.38
Y2: Design Schedule Index (%)	
Risk with working with the consultant firm	0.49
Technical Complexity	0.42
Project cost related complexity	0.44
Number of firms collaborating	0.49
Interdependencies of trades and tasks	0.3
Consultant Firm Selection	0.54
Y3: Construction Cost Index (%)	
Location Based Complexity	-0.32
Human Factor for employees during the construction process	-0.36
Consultant Firm Selection	0.39
Y4: Construction Schedule Index (%)	
Project Cost Related Complexity	-0.33
Community Impact	0.32
Human factors for end users	0.32
Y5: Number of Change Orders	
Completing project on budget and time	0.38
Political Risk	0.37
Complexity of project requirements	0.42
Project Cost related complexity	0.69
Number of firms collaborating	0.61
Interdependencies of construction trades and tasks	0.58
Design Procurement Method	0.39

Description	Correlation Coefficient
Consultant Firm Selection	0.47
Y6: Impact of Change Orders on Construction Cost	
Social Risk	-0.41
Consultant Firm Selection	0.65
Y7: Impact of Claims on Construction Cost	
Risk with working with consultant firm	-0.42
Complexity of project requirements	-0.38
Design Procurement Method	0.51
Consultant firm Selection	0.39
Construction Delivery method	0.5
Y8: Number of Claims	
Human Factor for employees during the construction process	0.32
Design Procurement method	0.41
Y9: Impact of Change Orders on Construction Schedule	
Technical Complexity	0.43
Community Impact	0.51
Design Procurement Method	0.34
Y10: Impact of Claims on Construction Schedule	
Human Factor for employees during the construction process	0.32
Project Type	-0.46
Construction Delivery Method	0.32
Design Procurement Method	0.43
Consultant Firm Selection	0.42
Y11: Number of NCRs	
Risk with working with the consultant firm	0.55
Location based complexity	0.39
Project Cost Related Complexity	0.35
Design Procurement Method	0.47
Consultant Firm Selection	0.34
Construction Delivery Method	0.5
Y12: Number of RFIS	
Completing Project on budget and time	0.4
Political Risk	0.48
Project Cost Related Complexity	0.64
Location based complexity	0.31
Interdependencies of trades and tasks	0.37
Human factors for end users	-0.35
Design procurement Method	0.38
Project Type	0.35
Consultant Firm Selection	0.36
Construction Delivery Method	0.66
Y13: Time taken to select the consultant firm once a request for a bid has been made public	
Risk of completing project on budget and time	0.38
Risk working with the consultant firm	0.41
Location based complexity	0.4

Description	Correlation Coefficient
Number of firms collaborating	0.31
Construction Delivery Method	0.3
Y14: Time taken to approve the final design scope, plans, schedule, and fees	
Political risk	0.35
Project cost related complexity	0.35
Number of firms collaborating	0.38
Design Procurement Method	0.35
Y15: Time taken to award the selected consultant to execute the PSA	
Risk working with the consultant firm	0.47
Location based complexity	0.31
Number of firms collaborating	0.36
Y16: The procurement process ensured a competitive and cost-effective process	
Social Risk	-0.34
Human factors for end users	-0.34
Project Type	0.54
Consultant Firm Selection	0.54
Construction Delivery Method	0.37
Y17: The selected procurement approach enhanced project effectiveness	
Political Risk	-0.33
Number of firms collaborating	0.32
Project Type	0.43
Consultant Firm Selection	0.5
Construction Delivery Method	0.3
Y18: The benefits of the procurement process outweighed associated risk	
Political Risk	-0.42
Social Risk	-0.31
Consultant Firm Selection	0.47
Project Type	0.66
Y19: The process addressed incomplete scope	
Political Risk	-0.34
Number of firms collaborating	0.43
Project Type	0.46
Construction Delivery Method	-0.38
Consultant Firm Selection	0.54
Y20: The resulting design concept and consultant performance were satisfactory	
Location based complexity	0.33
Sustainability aspects	0.44
Community Impact	0.63
Interdependencies of construction trades and risks	0.3
Human factors for employees during the construction process	0.48
Human factors end user	0.45
Consultant Firm Selection	049
Project Type	0.48
Y21: The resulting project quality and contractor performance were satisfactory	
Risk of Completing project on Time and Budget	-0.51
Complexity of project requirements	-0.31

Description	Correlation Coefficient
Sustainability Aspects	0.31
Consultant Firm Selection	0.59
Project Type	0.37
Design Procurement Method	0.33
Y22: The procurement approach promoted innovation and capacity building	
Completing project on Time and Budget	-0.52
Political Risk	-0.3
Interdependencies of construction trades and risks	0.43
Project Type	0.63
Consultant Firm Selection	0.5
Construction Delivery Method	0.38

APPENDIX C: Source Code

Part A: Source Code Model 1

```
install.packages("readxl")
install.packages('dplyr')
library(dplyr)
library("readxl")
library(stats)
library(DescTools)
library(Kendall)
library(ggpubr)
library("Hmisc")
library (corrplot)
library(ggplot2)
library(stringr)
#read excel file while setting directory
setwd("C:/Users/eltah/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
my_data<-read_excel("Results_Without_Missing_KNN_OrdinalCoding.xlsx", sheet= "Ordinal Coding (2)")
#checking data type
typeof(my_data)
class(my_data)
str(my_data)
attach(my_data)
col <- colorRampPalette(c("darkorange","beige", "steelblue"))(20)

# Storing Evaluation of Consultant Firm Qualifications and Project performance indices in a data frame by recalling column index number
dff0 <- ((my_data[,c(23,26,29,32,52:63)])
dff0 <- mutate_all(dff0, function(x) as.numeric(as.character(x)))
dff0[is.na(dff0)] = 0
dff0
#plotting correlation matrix using spearman of Consultant Firm Qualifications and Project performance indices
b<-cor(dff0,method = "spearman")
plot.new()
M<-cor(dff0)
head(round(M,2))
corrplot(b,type="lower", tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1,col=col,tl.cex=0.8, cl.cex=0.8)

# Storing Consultant Firm Qualifications and remaining performance outcomes in a data frame by recalling column index number
dff1 <- ((my_data[,c(33:44,52:57)])
dff1 <- mutate_all(dff1, function(x) as.numeric(as.character(x)))
dff1[is.na(dff)] = 0
dff1
#plotting correlation matrix using spearman for Consultant Firm Qualifications and remaining performance outcomes
plot.new()
M<-cor(dff1)
head(round(M,2))
plot.new()
```

```
d<-cor(dff1,method = "spearman")
corrplot(d,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1,col=col,tl.cex=0.75, cl.cex=0.75)


# Storing Consultant for performance outcomes indices and project comprehension and relevant experience and past performance  by recalling column index number
dff2 <- (my_data[,c(23,26,29,32,64:74)])
dff2 <- mutate_all(dff2, function(x) as.numeric(as.character(x)))
dff2[is.na(dff2)] = 0
dff2
#plotting correlation matrix using spearman for onsultant for performance outcomes indices and project comprehension and relevant experience and past performance
plot.new()
M<-cor(dff2)
head(round(M,2))
plot.new()
f<-cor(dff2,method = "spearman")
corrplot(f,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1,col=col,tl.cex=0.75, cl.cex=0.75)

# Storing Consultant for project comprehension and relevant experience and past performance and remaining performance outcomes by recalling column index number
dff3 <- (my_data[,c(33:44,58:74)])
dff3 <- mutate_all(dff3, function(x) as.numeric(as.character(x)))
dff3[is.na(dff3)] = 0
dff3
#plotting correlation matrix using spearman for Consultant Firm Qualifications and remaining performance outcomes
plot.new()
M<-cor(dff3)
head(round(M,2))
plot.new()
h<-cor(dff3,method = "spearman")
corrplot(h,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1.7,col=col,tl.cex=1.5, cl.cex=1.5)


# Storing Consultant for Overall   satisfaction and A/E qualifications  using Kendall  by recalling column index number
dff7 <- (my_data[,c(45:51,52:74)])
dff7 <- mutate_all(dff7, function(x) as.numeric(as.character(x)))
dff7[is.na(dff7)] = 0
dff7
#plotting correlation matrix using spearman overall satisfaction and A/E qualifications  using spearman  by recalling column index number
plot.new()
M<-cor(dff7)
head(round(M,2))
plot.new()
o<-cor(dff7,method = "spearman")
corrplot(o,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1,col=col,tl.cex=1.2, cl.cex=1.2)

#Correlation betweentime associated with procurement and qualifications
dff11 <- (my_data[,c(52:74, 84:86)])
```

```
dff11 <- mutate_all(dff11, function(x) as.numeric(as.character(x)))
dff11[is.na(dff11)] = 0
dff11
#plotting correlation matrix using spearman between time associated with procurement and qualifications
plot.new()
M<-cor(dff11)
head(round(M,2))
plot.new()
w<-cor(dff11,method = "spearman")
corrplot(w,type="lower",   tl.col = "black",method = "color",  addCoef.col = "black",number.cex= 0.7,col=col,tl.cex=0.75,  cl.cex=0.75)
```

Part B: Source Code Model 2

```
install.packages("readxl")
install.packages('dplyr')
library(dplyr)
library("readxl")
library(stats)
library(DescTools)
library(Kendall)
library(ggpubr)
library("Hmisc")
library (corrplot)
library(ggplot2)
library(stringr)
#read excel file  while  setting directory
setwd("C:/Users/eltah/OneDrive  - ualberta.ca/MSC/Research/QBS/Analysis")
my_data<-read_excel("Results_Without_Missing_KNN_OrdinalCoding.xlsx",  sheet= "Ordinal  Coding (2)")
#checking data type
typeof(my_data)
class(my_data)
str(my_data)
attach(my_data)
col <- colorRampPalette(c("darkorange", "beige",  "steelblue"))(20)


#  Correlation between between project performance outcomes and Project Risks,  Complexity, and social factors recalling  column index number
dff10 <- (my_data[,c(2:22,23,26,29,32:44)])
dff10 <- mutate_all(dff10, function(x) as.numeric(as.character(x)))
dff10[is.na(dff10)] = 0
dff10
#plotting correlation matrix using spearman between project performance outcomes and Project Risks, Complexity, and social factors
plot.new()
M<-cor(dff10)
head(round(M,2))
plot.new()
u<-cor(dff10,method = "spearman")
corrplot(u,type="lower",   tl.col = "black",method = "color",  addCoef.col = "black",number.cex= 1,col=col,tl.cex=1.2,  cl.cex=1.2)

```

```
# Correlation between between overall management satisfaction and Project Risks, Complexity, and social factors using Kendal
dff11 <- (my_data[,c(2:20,45:51)])
dff11 <- mutate_all(dff11, function(x) as.numeric(as.character(x)))
dff11[is.na(dff11)] = 0
dff11
#plotting correlation matrix using spearman between project performance outcomes and Project Risks, Complexity, and social factors
#number.cex= 7/ncol(Df)
plot.new()
M<-cor(dff11)
head(round(M,2))
plot.new()
w<-cor(dff11,method = "spearman")
corrplot(w,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 1,col=col,tl.cex=1.2, cl.cex=1.2)

#Correlation using spearman between time associated with procurement and project risks and stuff
dff12 <- (my_data[,c(2:20, 84:86)])
dff12 <- mutate_all(dff12, function(x) as.numeric(as.character(x)))
dff12[is.na(dff12)] = 0
dff12
#plotting Correlation Matrix using spearman between time associated with procurement and project risks and stuff
plot.new()
M<-cor(dff12)
head(round(M,2))
plot.new()
w<-cor(dff12,method = "spearman")
corrplot(w,type="lower",  tl.col = "black",method = "color", addCoef.col = "black",number.cex= 0.7,col=col,tl.cex=0.75, cl.cex=0.75)
```

Part C: Sample Source Code Model 3

```
install.packages("neuralnet")
install.packages("readxl")
install.packages("NeuralNetTools")
install.packages('dplyr')
install.packages("boot")
install.packages("plyr")

# load library
require(neuralnet)
library(dplyr)
library(stats)
library(DescTools)
library(Kendall)
library(ggpubr)
library("Hmisc")
library (corrplot)
library(ggplot2)
library(stringr)
library("readxl")
```

```
library(stringr)
library(nnet)
library(boot)
library(plyr)
#read excel file while setting directory
#setwd("C:/Users/eltah/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
setwd("C:/Users/eltahan.CONSTRUCTION/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
my_data<-read_excel("Bootstrap_Sample_.xlsx", sheet= "Sheet1")
attach(my_data)
#removing spaces in column names
names(my_data)<-str_replace_all(names(my_data), c(" " = ".", "," = ""))
colnames(my_data)
my_data <- mutate_all(my_data, function(x) as.numeric(as.character(x)))
my_data[is.na(my_data)] = 0
# Normalize dataset throuh max and min function
normalize <- function(x) { return ((x - min(x)) / (max(x) - min(x)))}

# DESIGN SCHEDULE INDEX cross validation where K is (Qualifications) the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
colnames(train.cv)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 20
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Design.Schedule.Index`~`Health.and.Safety.Processes`+`Cost.control`+`Subconsultant.Experience`+`Quality.Control.Experience`+`Inclusion.of.necessary.disciplines.and.experts`+`Approach.to.schedule.budget.and.quality...control`+`Approach.to.conflict.resolution`,data=train.cv, hidden=c(70,30),act.fct = "logistic",linear.output = FALSE)
  temp_test <- subset(test.cv, select = c(`Health.and.Safety.Processes`,`Cost.control`,`Subconsultant.Experience`,`Quality.Control.Experience`,`Inclusion.of.necessary.disciplines.and.experts`,`Approach.to.schedule.budget.and.quality...control`,`Approach.to.conflict.resolution`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  test.cv.r <- (test.cv$Design.Schedule.Index)*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  MSE.error[i] <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  PE.errorx<-ifelse (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
```

```
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<- (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)


# Design Cost Index cross validation where K is (Qualification) the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Design.Cost.Index`~`Project.management..experience`+`Design.innovation.and.value.engineering`+ `Identification.of.key.personnels.roles.and.responsibilities`,data=train.cv, hidden=c(20,40),act.fct = "logistic",linear.output = FALSE)
  temp_test <- subset(test.cv, select = c(`Project.management..experience`,`Design.innovation.and.value.engineering`,`Identification.of.key.personnels.roles.and.responsibilities`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
  test.cv.r <- (test.cv$Design.Cost.Index)*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
  MSE.error[i] <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  RMSE.error[i] <- (sum((test.cv.r - pr.nn)^2)/nrow(test.cv))^0.5
  PE.errorx<-ifelse (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<- (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)
```

Part D: Sample Source Code Model 4

```
install.packages("neuralnet")
install.packages("readxl")
install.packages("NeuralNetTools")
install.packages('dplyr')
install.packages("boot")
install.packages("plyr")

# load library
require(neuralnet)
library(dplyr)
library(stats)
library(DescTools)
library(Kendall)
library(ggpubr)
library("Hmisc")
library (corrplot)
library(ggplot2)
library(stringr)
library("readxl")
library(stringr)
library(nnet)
library(boot)
library(plyr)
#read excel file while setting directory
#setwd("C:/Users/eltah/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
setwd("C:/Users/eltahan.CONSTRUCTION/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
my_data<-read_excel("Bootstrap_Sample_.xlsx", sheet= "Sheet1")
attach(my_data)
#removing spaces in column names
names(my_data)<-str_replace_all(names(my_data), c(" " = ".", "," = ""))
colnames(my_data)
my_data <- mutate_all(my_data, function(x) as.numeric(as.character(x)))
my_data[is.na(my_data)] = 0
# Normalize dataset throuh max and min function
normalize <- function(x) { return ((x - min(x)) / (max(x) - min(x)))}


#DESIGN SCHEDULE INDEX cross validation where(characteristics) K is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
colnames(train.cv)
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
```

```
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Design.Schedule.Index`~`Risk.with.working.with.consultant.Firm`+`Technical.Complexity`+`Project.Cost.Related.Complexity`+`Number.Of.Firms..collaborating`+`Interdependencies.of.construction.trades.and.tasks`+`Consultant.Firm.Selection`,data=train.cv, hidden=c(10,40),act.fct = "logistic",linear.output = FALSE)
  temp_test <- subset(test.cv, select = c(`Risk.with.working.with.consultant.Firm`,`Technical.Complexity`,`Project.Cost.Related.Complexity`,`Number.Of.Firms..collaborating`,`Interdependencies.of.construction.trades.and.tasks`,`Consultant.Firm.Selection`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  test.cv.r <- (test.cv$Design.Schedule.Index)*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  MSE.error[i]  <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  RMSE.error[i]  <- (sum((test.cv.r  - pr.nn)^2)/nrow(test.cv))^0.5
  PE.errorx<-ifelse  (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<-  (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)

# Design  Cost Index cross validation where K (charcter)is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
colnames(train.cv)
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Design.Cost.Index`~ `Risk.with.working.with.consultant.Firm`+`Technical.Complexity`+`Interdependencies.of.construction.trades.and.tasks`+`Sustainability.Aspects`+`Human.Factor.for.employees.during.the.construction.process`,data =train.cv, hidden=c(50,30),act.fct = "logistic",linear.output  = FALSE)
```

```
  temp_test <- subset(test.cv, select = c(`Risk.with.working.with.consultant.Firm`,`Technical.Complexity`,`Interdependencies.of.construction.trades.and.tasks`,`Sustainability.Aspects`,`Human.Factor.for.employees.during.the.construction.process`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
  test.cv.r <- (test.cv$Design.Cost.Index)*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
  MSE.error[i]  <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  RMSE.error[i]  <- (sum((test.cv.r - pr.nn)^2)/nrow(test.cv))^0.5
  PE.errorx<-ifelse  (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<-  (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)

# CONSTRUCTION  COST  INDEX cross validation where K is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
colnames(train.cv)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Construction.Cost.Index`~`Location.Based.Complexity`+`Human.Factor.for.employees.during.the.construction.process`+`Consultant.Firm.Selection`,data=train.cv, hidden=c(80,10),act.fct = "logistic",linear.output  = FALSE)
  temp_test <- subset(test.cv, select = c(`Location.Based.Complexity`,`Human.Factor.for.employees.during.the.construction.process`,`Consultant.Firm.Selection`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Construction.Cost.Index)-min(my_data$Construction.Cost.Index))+min(my_data$Construction.Cost.Index)
  test.cv.r <- (test.cv$Construction.Cost.Index)*(max(my_data$Construction.Cost.Index)-min(my_data$Construction.Cost.Index))+min(my_data$Construction.Cost.Index)
  MSE.error[i]  <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
```

```
  PE.errorx<-ifelse  (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<-  (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)

#Construction Schedule Index cross validation where K ( character) is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
colnames(train.cv)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Construction.Schedule.Index`~`Project.Cost.Related.Complexity`+`Community.Impact`+`Human.Factors.for.end.users`,data=train.cv, hidden=c(70,30),act.fct = "logistic",linear.output  = FALSE)
  temp_test <- subset(test.cv, select = c(`Project.Cost.Related.Complexity`,`Community.Impact`,`Human.Factors.for.end.users`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Construction.Schedule.Index)-min(my_data$Construction.Schedule.Index))+min(my_data$Construction.Schedule.Index)
  test.cv.r <- (test.cv$Construction.Schedule.Index)*(max(my_data$Construction.Schedule.Index)-min(my_data$Construction.Schedule.Index))+min(my_data$Construction.Schedule.Index)
  MSE.error[i]  <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  PE.errorx<-ifelse  (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<-  (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
```

```
mean(MAPE.error)
MAPE.error
```

Part E: Source Code Model 5

```
install.packages("neuralnet")
install.packages("readxl")
install.packages("NeuralNetTools")
install.packages('dplyr')
install.packages("boot")
install.packages("plyr")

# load library
require(neuralnet)
library(dplyr)
library(stats)
library(DescTools)
library(Kendall)
library(ggpubr)
library("Hmisc")
library (corrplot)
library(ggplot2)
library(stringr)
library("readxl")
library(stringr)
library(nnet)
library(boot)
library(plyr)
#read excel file while setting directory
#setwd("C:/Users/eltah/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
setwd("C:/Users/eltahan.CONSTRUCTION/OneDrive - ualberta.ca/MSC/Research/QBS/Analysis")
my_data<-read_excel("Bootstrap_Sample_.xlsx",sheet= "Sheet1")
attach(my_data)
#removing spaces in column names
names(my_data)<-str_replace_all(names(my_data), c(" " = ".", "," = ""))
colnames(my_data)
my_data <- mutate_all(my_data, function(x) as.numeric(as.character(x)))
my_data[is.na(my_data)] = 0
# Normalize dataset throuh max and min function
normalize <- function(x) { return ((x - min(x)) / (max(x) - min(x)))}

#DESIGN SCHEDULE INDEX cross validation where(Qualification+character) K is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
colnames(train.cv)
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
```

```
maxmindf
for(i in 1:k){
  index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
  train.cv <- maxmindf[index,]
  test.cv <- maxmindf[-index,]
  test.cv
  nn<-neuralnet(`Design.Schedule.Index`~`Health.and.Safety.Processes`+`Cost.control`+`Subconsultant.Experience`+`Quality.Control.Experience`+`Inclusion.of.necessary.disciplines.and.experts`+`Approach.to.schedule.budget.and.quality...control`+`Approach.to.conflict.resolution`+`Risk.with.working.with.consultant.Firm`+`Technical.Complexity`+`Project.Cost.Related.Complexity`+`Number.Of.Firms..collaborating`+`Interdependencies.of.construction.trades.and.tasks`+`Consultant.Firm.Selection`,data=train.cv, hidden=c(10,40),act.fct = "logistic",linear.output  = FALSE)
  temp_test <- subset(test.cv, select = c(`Health.and.Safety.Processes`,`Cost.control`,`Subconsultant.Experience`,`Quality.Control.Experience`,`Inclusion.of.necessary.disciplines.and.experts`,`Approach.to.schedule.budget.and.quality...control`,`Approach.to.conflict.resolution`, `Risk.with.working.with.consultant.Firm`,`Technical.Complexity`,`Project.Cost.Related.Complexity`,`Number.Of.Firms..collaborating`,`Interdependencies.of.construction.trades.and.tasks`,`Consultant.Firm.Selection`))
  pr.nn = neuralnet::compute(nn,temp_test)
  pr.nn <- pr.nn$net.result*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  test.cv.r <- (test.cv$Design.Schedule.Index)*(max(my_data$Design.Schedule.Index)-min(my_data$Design.Schedule.Index))+min(my_data$Design.Schedule.Index)
  MSE.error[i]  <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
  RMSE.error[i]  <- (sum((test.cv.r  - pr.nn)^2)/nrow(test.cv))^0.5
  PE.errorx<-ifelse  (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
  MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
  datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
  PE.error[i]<-mean(PE.errorx)
  pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<-  (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)

#Design  Cost Index cross validation where K (Qualification+charcter)is the number of folds amd then we use 90% of the data for training and 10% for testing for each fold
set.seed(450)
PE.error <- NULL
MSE.error <- NULL
RMSE.error <- NULL
MAPE.error<-NULL
k <- 40
library(plyr)
pbar <- create_progress_bar('text')
pbar$init(k)
maxmindf <- as.data.frame(lapply(my_data, normalize))
maxmindf
colnames(train.cv)
for(i in 1:k){
```

```
index <- sample(1:nrow(my_data),round(0.9*nrow(my_data)))
train.cv <- maxmindf[index,]
test.cv <- maxmindf[-index,]
test.cv
nn<-neuralnet(`Design.Cost.Index`~`Project.management..experience`+`Design.innovation.and.value.engineering`+`Identification.of.key.personnels.roles.and.responsibilities`+`Risk.with.working.with.consultant.Firm`+`Technical.Complexity`+`Interdependencies.of.construction.trades.and.tasks`+`Sustainability.Aspects`+`Human.Factor.for.employees.during.the.construction.process`,data=train.cv, hidden=c(10,30),act.fct = "logistic",linear.output = FALSE)
temp_test <- subset(test.cv, select = c(`Project.management..experience`,`Design.innovation.and.value.engineering`,`Identification.of.key.personnels.roles.and.responsibilities`,`Risk.with.working.with.consultant.Firm`,`Technical.Complexity`,`Interdependencies.of.construction.trades.and.tasks`,`Sustainability.Aspects`,`Human.Factor.for.employees.during.the.construction.process`))
pr.nn = neuralnet::compute(nn,temp_test)
pr.nn <- pr.nn$net.result*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
test.cv.r <- (test.cv$Design.Cost.Index)*(max(my_data$Design.Cost.Index)-min(my_data$Design.Cost.Index))+min(my_data$Design.Cost.Index)
MSE.error[i] <- sum((test.cv.r - pr.nn)^2)/nrow(test.cv)
RMSE.error[i] <- (sum((test.cv.r - pr.nn)^2)/nrow(test.cv))^0.5
PE.errorx<-ifelse (test.cv.r==0,(test.cv.r-pr.nn),((test.cv.r-pr.nn)/test.cv.r))
MAPE.error[i]<-sum(abs(PE.errorx))/nrow(test.cv)
datan<-data.frame(PE.errorx,test.cv.r,pr.nn)
PE.error[i]<-mean(PE.errorx)
pbar$step()
}
datan # predicted and actualvalues
MSE.error<-mean(MSE.error)
RMSE.error<- (MSE.error)^0.5
RMSE.error
MSE.error
mean(PE.error)
mean(MAPE.error)
```