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Project Leanness Score: A Machine Learning Approach

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Project Leanness Score:
A Machine Learning Approach

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Dedication

This thesis, along with everything else I do, is dedicated to my late grandparents Roushdy Demian and Nawal George. You are my guardian angels in heaven, I hope I am making you proud.

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Abstract

The construction industry is known to have several inadequacies in resource utilization leading to cost and schedule overruns. One of the popular recent methods that attempts to eliminate these inadequacies is lean construction principles, techniques and tools. Lean construction is a philosophy, backed with principles and tools, aiming at maximizing value, eliminating waste, optimizing efficiency, and seeking continuous improvement. Lean construction techniques (such as pull planning, just-in-time delivery, fail safe for quality, etc.) are widely researched and well developed. However, their implementation in construction sites is tricky as their success depends on several other factors such as the level of trust, the use of supporting technologies, and the resistance to cultural change. In other words, just by implementing lean construction tools does not guarantee reduction in cost and time overruns. There is a gap when it comes to identifying the factors that support the success/failure of implementing lean construction tools, and quantifying the impact of those factors to the actual performance of construction projects.

The goal of this research is to develop and benchmark a scoring system that utilizes lean principles to evaluate the "leanness" of construction projects and predict their performance. To achieve such goal, the methodology of the research follows a series of six steps. First is identifying the key factors that influence the "leanness" of construction projects. Second, determining the significance and relative importance of the identified factors through an expert-based survey. Third, developing a novel leanness score using the established relative importance of the factors. Fourth, benchmarking the leanness score representing the industry's performance through collecting extensive project data from 30 construction projects. Fifth, training and validating models using machine learning algorithms such as regression, decision trees, and artificial neural networks to predict the schedule and budget performance of construction projects using the factors of the leanness score. Lastly, developing a user-friendly tool that enables companies to easily calculate the leanness score of their projects, compare it to the benchmarks, and predict their schedule and cost performance.

The outcomes of this research fill the existing gap since it aims to develop a leanness index and link it to project performance. Moreover, it presents a detailed level of performance assessment through breaking down the leanness score and indicating areas of strength and weakness in the project. Also, the developed benchmarking scale enables companies to compare their level of leanness to that of other companies in the industry. In addition, the developed multiclass classification neural networks model can predict and categorize project

schedule and budget performance with an accuracy of 96% and 94% respectively. With this, companies will be able to benchmark the performance of their projects, pinpoint the areas of strengths and weaknesses with respect to the benchmarks, and take necessary actions to meet industry practices. Thus, improving the overall quality of construction projects, decreasing overruns.

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Chapter 1. Introduction

1.1 Background Information

Construction projects are challenging to manage due to their complex nature. Because of that, construction projects have been known to go beyond their scheduled duration and planned budget more often to the extent that delays and cost overruns are the norm rather than the exception (Sterman 2010). In fact, it was reported in a global construction survey that over 50% of engineering and construction professionals report one or more underachieving projects in a year (Armstrong et al. 2016). According to 69% of owners, the biggest reason for project underperformance is poor contractor performance (Armstrong et al. 2016). Mismanagement in construction projects leads to schedule slippage, which causes 66% of contractors to incur extra costs for overtime and second shifts in order to finish on schedule; despite these efforts, 50% of contractors still need to extend the project end date (Hamzeh et al. 2016). Hence, projects are completed over budget and behind schedule. Other research efforts indicate that 75% of construction projects exceed their original deadlines and 69% go above budget (Kliment, 2015).

The fact that most construction projects are over budget and behind schedule means that there is a waste of some kind taking place. Over the years, engineers are constantly trying to analyze and improve on the conventional building methods in order to cut time, cost and upgrade the quality of construction projects. One of the methods of process optimization widely used nowadays in the construction field is lean construction. This methodology aims to remove any part of a process that does not bring value to the customer. The process simply focuses on dividing the activities needed to complete a project into two categories, value added activities and non-value-added activities (El-Sawalhi et al. 2018). Lean principles are implemented to remove and reduce no value-added activities to the utmost minimum in order to deliver an end product that is up to the customer's specifications with less cost, time and waste (Akinradewo, et al. 2018). Lean construction has been gaining attention from companies and professionals in the field since its introduction in the early 1990s (Mughees et al. 2020). The reason for that is that the implementation of lean aids in overcoming challenges such as productivity loss (Koskela, 1992) waste generation (Diekmann et al. 2004), and environmental issues (EPA, 2018).

Effective implementation of lean construction leads to outcomes that have been described by some authors as "revolutionary" (Albalkhy et al. 2021). Such outcomes include cost savings, decrease in project duration, improved safety measures, reduction in accidents on site, sustainability awareness, reduced waste generation, enhanced inventory management, higher labor productivity and improved customer satisfaction (Ko, 2010; Farrar et al., 2004; Mossman, 2009; Simonsson, 2007; Mohan, 2005; Salem et al., 2006; Conte et al., 2001). Frequent employment of lean practices in construction projects have been found to make projects three time more likely to be completed ahead of schedule and two times more likely to be completed under budget (Dodge and Analytics data, 2016). This was further validated by lean experts in the field, where 70% of 95 professionals acknowledged that implementing lean techniques led to improved performance and waste reduction (Mcgraw Hill, 2013). The effect of applying lean was quantified in case studies that showed that lean construction has shortened project schedule by 6–25% (Ballard et al., 2007; More et al., 2016; Erol et al., 2017), saved cost by 5–50% (Ballard et al., 2007) and increased productivity by 5–50% (Locatelli, 2013).

Lean construction affects both the contractor and the owner's sides. From the contractor's side, it improves the cash flow as money is being allocated correctly with minimum wastage (Akinradewo et al. 2018). Also, it enhances productivity and asset utilization which leads to increase in profit (El-Sawalhi et al. 2018). Moreover, it improves the contractor-owner relationship as the owner gets their intended value out of the project (El-Sawalhi et al. 2018). As for the owner's benefits, they are able to provide their customers with a consistent quality of product that is suitable for their needs. Also, construction time and cost are reduced without sacrificing quality (Ballard, 1999). Such benefits have encouraged countries such as USA, UK, Brazil, Chile, Peru, Ecuador, Venezuela, Finland, Denmark, South Korea, Singapore and Australia to implement lean and they are now considered the leading countries in adopting lean practices (Ballard et al., 2003; Johansen et al., 2007; Jørgensen et al., 2008).

It is important to note that the aforementioned benefits are only reaped by the project based on how well the employees implement lean techniques. According to Salem et al. (2006), proper implementation of lean techniques goes beyond the techniques themselves. In order to be able to get the maximum benefits of lean, there has to be a continuous change in employees' behavior. Such behavior included team work, active communication and high levels of visualization. The fact that project performance improvement is directly linked to how well lean techniques are implemented leads to a set of intriguing questions. The first is what are the factors that if applied frequently and efficiently entitle a project to be lean? Additionally, how can the quality of implementing such factors be measured in a construction project? How are lean factors related to project performance and lastly, how is project leanness linked to performance in terms of the project's schedule and budget?

These questions shed a light on the knowledge gap that this research intends to fill. This is implemented through extensively studying the different factors that impact lean implementation, followed by the development of a novel lean index to measure the "leanness" of projects, then a detailed investigation on how project performance is affected by such lean factors.

1.2 Research Goal, Objectives, and Merits

The goal of this research is to develop and benchmark a scoring system that utilizes lean principles to evaluate the "leanness" of construction projects and predict their performance. The objectives are:

(1) identifying the key lean factors that impact the leanness of projects;
(2) determining the relative importance of these factors with respect to construction projects;
(3) developing a scoring index that measures the leanness of construction projects;
(4) benchmarking construction projects based on the leanness index, and
(5) developing a machine learning model for predicting project performance based on its implementation of lean strategies.

The outcomes of this research fill the existing gap since it is the first to develop a leanness index and link it to project performance. The research will help project participants to assess their management practices and pinpoint the areas of strengths and weaknesses through comparing their leanness index to the identified benchmarks. Finally, the developed machine learning model, which is processed to a user-friendly tool, will enable project managers to predict the cost and schedule performance based on the employed management practices; thus, aiding in decision-making and improving the overall performance of construction projects.

1.3 Thesis Organization and Structure

This research consists of seven chapters described briefly through the following:

1. Chapter 1 provides background information about the research point of departure and describes the goals, objectives and significance of this research.
2. Chapter 2 summarizes the literature found on the different lean construction techniques and their effectiveness in construction projects, and summarizes the current project scoring systems body of knowledge; ending with describing the knowledge gap.
3. Chapter 3 outlines the utilized research methodology.
4. Chapter 4 discusses the process of identifying the key lean factors and developing the

project leanness score and benchmarking scale.

5. Chapter 5 employs the established project leanness score in developing a project performance prediction model through different machine learning algorithms.
6. Chapter 6 compiles the project leanness score along with the benchmarking scales established and showcases them in a user-friendly tool for construction companies to self-rate their performance. The tool also indicates areas of strength and weakness for the user to use as a guiding reference when setting recovery plans and company objectives.
7. Chapter 7 summarizes the research findings in the conclusion, discusses research limitations and recommendations for future research.

Chapter 2. Literature Review

This chapter is divided into four sections, each representing a topic in lean construction. The sections include a detailed description, analysis and critique of the literature found on the topic. The first section discusses how the original lean production concepts were adapted to fit the construction industry. It also addresses the fundamental differences between production and construction and how that affects the implementation of lean tools. Secondly, a description of the most used lean construction techniques and tools implemented globally is presented. After explaining the different techniques used, a section is dedicated to demonstrate the effectiveness of lean construction techniques. This section is important as it exemplifies the benefits along with the limitations of each lean technique when it comes to implementing it in construction sites. It also shows the factors affecting the correct implementation of lean tools and discusses ways on how to overcome them. Finally, literature findings of the previously developed construction-related scoring indices are presented and a summary of the research establishing lean construction rating systems is done. The chapter concludes with a statement describing the problem statement and knowledge gap that this research is tackling.

2.1 Moving from Lean Production to Lean Construction

Lean construction principles and techniques were adapted through applying the original lean thinking principles that were initially implemented in Toyota Production Systems (TPS) (Becker, 1998). Originally, there were five main principles in lean thinking: value identification, value stream mapping, waste elimination, customer pull and pursuit for perfection (Womack et al., 1996). There are many fundamental differences between a production process and a construction process. These differences, which are summarized in Table 1 below, demand for an appropriate adjustment of the traditional lean production tools in order for the tools to achieve desired results when applied to construction projects.

Table 1: Differences between manufacturing and construction industry (Paez et al. 2005)

Aspects	Construction industry	Manufacturing industry
Duration (life cycle)	Short	Long
Nature	One-of-a-kind nature	Repetitive
Work Station	Transient	Stable
Material components	Non-standardized	Standardized
Material supply	Schedule-driven	Order-driven
Safety provision	Less enforced	Highly enforced
Labour force	Seasonal, low job security	Not seasonal, higher employment security
Wages	Vary depending on skill, experience, and employers	More stable wage policies
Environment	Productivity influenced by the change in environment	Productivity less influenced by the change in environment
Assembly and production	final production is assembled in situ	Within the factory
Technology	Low level of automation, prefer not to use	Better and advanced
Quality	Related to product conformance; Rework is common	More closely to process control; Rework is generally avoided
Owner involvement	Highly involved	Less involved
Culture	Ill-defined, site personnel know nothing of company's management philosophy	Clearly defined so that staff are conscious of it
Regulatory intervention	Design solution and many work phases in a construction project are subject to checks and approvals by regulatory authorities	Less subject to checks and approvals

Source: Ball (1988); Koskela (1992); Low and Chan (1997); Oglesby, et al. (1989); Salem et al. (2006); Riley and Clare-Brown (2001); Winch (2003)

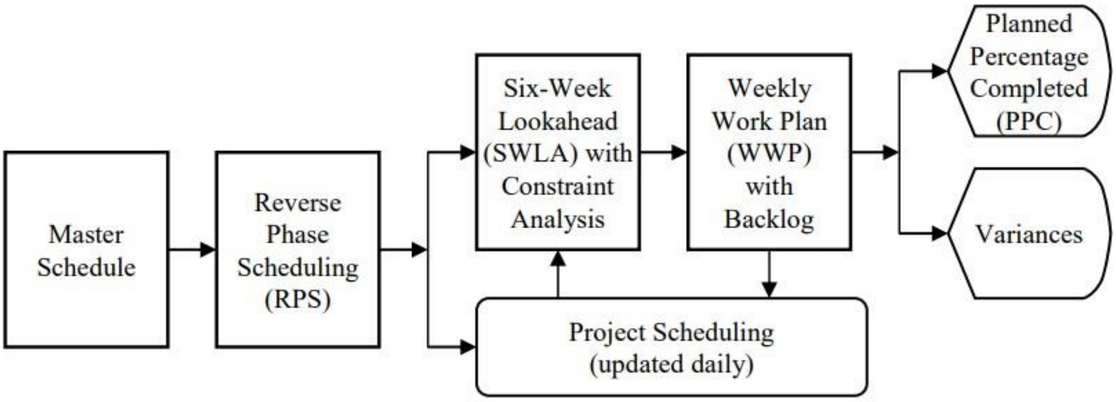
According to Paez et al. (2005), the transition from lean production to lean construction tools was done in three forms. The first form is adaptation, in which it is argued that lean construction techniques were first adapted as is from lean production techniques. Were the techniques that were applicable to the construction industry without any alterations were first implemented. An example of such adaptation is the Kanban cards system implementation in construction sites. The direct execution of the tools helped in understanding the difference between production and construction; which then gave room for analysis and paved the way to expansion. Where it is said to be the second form, the lean production techniques were expanded to include techniques that fit the construction industry. An example of such expansion would be the development of the and on system which involved only visual inspection of defective parts to include visualization of material and workflow. The third level included introducing new lean techniques fit for construction implementation. Such new techniques included the last planner system (LPS) which was developed in early 1990s by Glenn Ballard and Gregory Howell and has quickly become one of the most fundamental lean construction tools (Pasquire et al. 2016). Both of them developed a tool that helps in scheduling the construction sequence utilizing the reverse phase schedule. In the years that followed, several lean construction techniques were further developed and modified. According to Suresh et al. (2011), there are nine main techniques and tools of lean construction that are developed. These nine tools are as follows: Last planner system (LPS), daily huddle meetings, increased visualization, off-site prefabrication, 5s, fail safe, root cause analysis, first run study and Just in time. It is important to note that these techniques are not meant to be implemented all together, however they are used according to the project's needs and requirements. Moreover, not all techniques are effective when implemented on site as several of them require modifications and intense training to construction workers in order to yield the intended results. An explanation to each method and its effectiveness on site will follow later on in this chapter. A detailed explanation will follow in the below parts of this chapter

2.2 Lean Construction Techniques and Tools

Lean construction is a philosophy of waste elimination, adding value, and continuous improvement rather than just an implementation of a set of tools (Ballard et al., 2007). Lean philosophy aims to primarily eliminate non-value-added activities to a project (Conte et al., 2001). This is done through repetitive iterations that not only aim to advance new technical approaches, but also develop the soft skills and intellect of employees to be able to carry on the philosophy to get the desired end result (Diekmann et al., 2004). Having this philosophy established, there are various tools that aid in implementing such philosophy. The following is a summary of the key lean construction tools:

2.2.1. Last Planner System (LPS)

The last planner system (LPS) is a tool that works on optimizing the flow of work. It operates using the “pull” planning instead of the traditional “push” planning (Ballard, 1999). Where the pull technique works backwards by matching the workflow, capacity and productivity to develop construction methods (Ballard, 1999). While the push method takes traditional construction methods and creates a schedule based on it (Ballard, 1999). Utilizing LPS allows for creating a realistic schedule instead of an overly optimistic or pessimistic one (Pasquire et al., 2016). This schedule is based on collaborative input from the project’s stockholders. The LPS approach helps in delivering projects on time, reducing costs and improving employer’s satisfaction (Salem et al., 2005). In LPS, planners work on developing a schedule that facilitates workflow. The sequence of LPS technique, as explained by Salem et al. (2005), shown in Figure 1 goes as follows: master schedule, reverse phase schedules (RPS), six-week lookahead (SWLA), weekly work plan (WWP) and planned percentage complete (PPC). As seen from the sequence, LPS is designed to tackle project schedule from a very broad level narrowing down to the detailed activity level. The technique also allows for constant monitoring of the project’s progress through the PPC.



1.

Figure 1: The sequence of Last Planner Process (Salem et al. 2005)

The efficiency and practicality of the LPS technique were assessed in previous research. It was found that the PPC values usually range from 30-70% using traditional planning however, implementing LPS raises them up to 90% (Ballard, 1999). LPS contributes not only to improved planning efficiency of the project, but also improved overall project performance and delivery (Tokede, 2016). The tool is currently being utilized in several construction projects as it is becoming known for its promising end results and efficiency. The available literature is rich with case studies of projects were LPS was used. Such case studies include worldwide projects such as, but not limited to, India (Vignesh, 2017), New Zealand (Fuemana et al., 2013) and Nigeria (Ahiakwo et al., 2013). Where they discuss the practicality, results and challenges associated with implementing LPS in construction projects.

2.2.2. Daily Huddle Meetings

Daily huddles are meetings held on a daily basis with employees, workers and managers from all involved disciplines in the project. The main aim of these meetings is to improve communication and coordination within teams and between teams across different disciplines (Salem et al. 2005). In the meetings, workers update each other on the status of the project and discuss briefly the activities to be done on that day. This allows for improving the overall morale of the project, as employees feel involved and it increases their sense of ownership to the project. The daily meetings also give indications to managers about the areas where employees struggle the most with and can help give insight to providing solutions. This improves coordination within the entity, also helps the communication between the different departments (Salem et al. 2005).

2.2.3. Increased Visualization

This tool follows the *Kanban* Japanese system, where it focuses on delivering information through signs, labels and infographics. This tool helps workers remember key information as having the signs and images around the site provides for an easy way to transmit the important information to the brain. (Salem et al. 2005)

2.2.4. *Off-site Fabrication*

Off-site fabrication is the process of prefabricating structural elements away from the construction site and having them delivered to site when and where they are needed. This affects positively several elements of the construction process. For example, as the number of labors, equipment and material present on site is reduced, traffic and maneuvering gets enhanced and becomes more safe on site (Pasquire et al. 2002). It also reduces material storage area, optimizing the usage of spaces. In addition, it increases flexibility and efficiency especially when using the just in time technique (Pasquire et al. 2002. Moreover, having elements fabricated away from the site improves its quality and reduces errors done (Pasquire et al. 2002). This provides for good quality control and improves customer satisfaction (Pasquire et al. 2002).

2.2.5. *5S*

The advancement of lean principles led to the development of 5 lean concepts that are now widely referred to as 5S. The name comes as an abbreviation of the 5-step process that is used when it comes to increasing overall productivity and efficiency. The 5S process aims to optimize construction through eliminating waste, avoiding unneeded activities and unnecessary items (Hiwale et al., 2018). These 5 steps are sort, set in order, shine, standardize and sustain. Sort is the first step of the process, where unnecessary and unwanted items and workflow steps are identified and eliminated. This is applied in construction through the context of removing unnecessary equipment, materials and redundant activities (Yang et al., 2004). That way, only the equipment and materials that are constantly in use are allocated in the site and unneeded materials and equipment are transported out of the site freeing up site work area and storage space. The second step is set in order, where it requires things to be at the right place in the right time in order to minimize waiting time. This is exemplified through having a procurement strategy that is constantly updated and followed according to the progress of the site in order for materials and equipment to arrive at the right time (Hiwale et al., 2018). Additionally, an efficient site layout aids in having things in the right place minimizing movement on site and therefore decreasing time wastage. Then comes the third step, shine; were continuous waste removal and maintenance is done. After that, comes the standardization step were previously established norms and practices are standardized. For example, in construction projects, standardize can be done in regulating inspection processes and homogenizing project reports formatting to facilitate easier and faster progress (Hiwale et al., 2018). The last step is to sustain, where employees have to keep a constant effort in sustaining the established 5S process in order to fully realize the benefits of implementing the 5S technique.

2.2.6. Fail Safe for Quality and Safety

The idea of fail-safe is based on developing a quality control system that prevents defective work from flowing in the construction process. This is done through visual inspection, constant monitoring and proper transportation, storage and installation of materials. Fail safe for safety is done through utilizing safety assessment tools to remove potential hazards. Both approaches allow for prevention of defects and hazards (Salem et al. 2005)

2.2.7. Root Cause Analysis

Root cause analysis is a systematic iterative process that deals with identifying the origin of an error and works on eliminating this source of the error (Sarkar et al. 2013). Causes of errors should be actionable, where as soon as they are discovered, a plan is done with clear action points to prevent the repetition of this error. The goal of root cause analysis is to identify what caused the error and how this error happened. Then, corrective measures are done to tackle the original root cause and not just the superficial source of error. This helps in establishing a permanent solution to problems that arise. The repetition of corrective actions also optimizes the construction process as it continuously improves. Root cause analysis can be applicable in construction on productivity issues, risk analysis, human error, and risk mapping (Sarkar et al. 2013).

2.2.8. First Run Studies

This lean tool is utilized in order to continuously improve and re-develop processes involved in the project. It works on studying a certain process with great detail and developing new alternative methods of doing the work (Salem et al. 2005). This is done through analyzing productivity rates, construction methods, coordination and overlapping of the different functions involved. First run studies are performed in a cycle made up of 4 steps (Salem et al. 2005). The first step is “plan”; where the process under study is chosen, the steps in the process are analyzed and feedback of people working on the process is taken. The second step is “do”, in which new ideas for performing the work are tried. Then, comes the third step which is check, where a review of the ideas is done and checked to compare what was planned to what actually happened. The last step is “act”, where the improved method is finalized, the steps are explained and communicated to the team and the new method is implemented (Salem et al. 2005).

2.2.9. Just In Time (JIT)

One of the most widely known lean tools is the Just-In-Time (JIT) tool (Groenevelt, 1993). JIT simply works on eliminating all types of waste in order to improve productivity. The method aims to achieve the ideal state of having the right amount of input materials ready when and where they are needed. JIT system works through incorporating several lean tools at the same time (Pheng et al., 1999). The first lean tool utilized in JIT is the pull planning tool where the desired end result of the project determines how it will be planned. This is opposed to push planning where the project schedule is built based on an anticipation of the required duration of each activity. JIT also incorporates the Kanban system where materials, equipment and tools are labeled according to their type, activities they are used in and where and how to store them. Kanban improves the overall site coordination, allows for smooth movement between the consecutive stages of construction and reduces wait time (Pheng et al., 1999). Other important elements that JIT regulates are setup time and production smoothing. Where construction activity time is planned to include the setup time of tools, equipment and machines required to efficiently carry out activities without wasting time. Moreover, production smoothing makes sure that the site workspace is organized allowing for a steady productivity rate of repetitive activities. Lastly, JIT works on standardizing operations where repetitive activities and processes are assigned to the same crews. This helps in reducing variability in production time, improving workflow, identifying unnecessary people, material or machinery and recognizing sources of errors hence improving overall quality (Groenevelt, 1993). Several construction projects incorporated JIT in regulating building inventory management (Akintoye, 1995), increasing the project’s productivity and quality (Pheng et al., 2011) and facilitating a smooth workflow of construction activities (Hussein et al., 2021).

2.3 Effectiveness of Lean Construction Techniques

As previously stated, the existing literature shows that lean construction techniques and tools are gaining momentum across the world. The popularity of lean construction arises from the promising results of implementing lean (Ballard et al., 2003). As a natural response to such results, 23% of construction firms worldwide have reported their intention to implement lean construction techniques to in order improve project performance (Scott, 2021).

Lean construction tools require extensive research and planning prior to implementing them on site. The research presented herein shows that despite the extensive efforts done in developing lean tools, some still require modifications in order to demonstrate the desired results. The study conducted by Salem et al. (2005) assesses six different lean construction tools based on their implementation in a university garage project and suggests areas of improvement for each tool as seen in Table 2. The last planner system showed promising results as the project finished earlier than its planned time. The percent plan complete (PPC) values of the project were ranging between 70% to 90% in which the author attributed such high values to the last planner's commitment to the project. This shows that successful implementation of lean tools relies not only on the lean tools themselves but also on the employee's conduct. The increased visualization tool helped in showing the progress of the project through updating the visual signs after every milestone. The signs also improved the commitment and morale of employees. As for the effectiveness of daily huddle meetings, the evaluation showed that more than 80% of planners and 67% of workers found value in the meetings hence, proving its effectiveness. The first run studies showed astounding results proving that productivity can be increased from 53% to 62% without additional investment. This can be done through simply placing the material close to the work area and having a standard crew perform the activity. Finally, fail safe for quality and safety, OSHA standards were followed and the percentage of safe work improved by 27.8%. in conclusion, implementation of lean tools was beneficial to the project as the project's actual duration was reduced and the overall communication and commitment to the project was improved (Salem et al., 2005)

Table 2: Lean tools recommended for future use (Salem et al. 2005)

Enabler	Status	Recommendations
Last Planner	Ready to be implemented	1.Emphasis on Reverse Phase Scheduling 2.Emphasis on variance Analysis
Visualization	To be implemented with some modifications	1. Integrated approach 2. Safety-Quality-Housekeeping
Daily Huddle Meetings	To be implemented with some modifications	Change frequency of the meetings with smaller groups
First Run Studies	To be implemented with some modifications	1 Integrate with scrum meetings (Tool Box Meetings) 2 Document learning process
The 5s Process	To be implemented with some modifications	Housekeeping can be address with Increased Visualization
Fail Safe For Quality and Safety	To be re-examined	1 Use Plan Conditions and Work Environment 2 Use Quality at the Source

2.3.1. Benefits of implementing lean construction

When assessing the effectiveness of lean construction techniques, one must look at the benefits that are associated with implementing lean techniques in real life construction sites. According to Kilpatrick (2003), lean construction techniques provide improvements in three main aspects; strategic, administrative and operational. The strategic aspect is improved through better client-contractor relationship and client satisfaction. This allows companies to have a good reputation and therefore increases their market share. The administrative improvements include reducing redundant processes, standardizing repetitive tasks and homogenizing project reports are all benefits associated with implementing lean (Kilpatrick, 2003). The operational aspect is improved as the productivity and quality of work increases, site space is more efficiently utilized and flow of work is improved (Kilpatrick, 2003 and Ogunbiyi et al., 2014). Other authors were in agreement with the operational benefits of lean construction and they were quantified as follows; increased labor productivity enhancement by 43%, reduction in cycle time by 41% and process efficiency enhancement by 27% (Abbasian-Hosseini et al., 2014). There are other intangible advantages to implementing lean construction such as improved corporate image, improved project delivery and increasing client satisfaction through delivering projects that are to up client expectations (Ogunbiyi et al., 2014). Lastly, authors also attested improvement in the environmental quality of projects that regularly implement lean construction (Ogunbiyi et al., 2014 and Bajjou et al., 2018). It is important to note that there are a number of other benefits associated with lean construction, however each project realizes these benefits differently depending on the frequency and proficiency of utilizing the tools.

2.3.2. Last Planner System Challenges and Proposed Implementation Strategies in Egypt

The following is a summary of a case study by Abdel hamid et al. (2019) where they studied the effectiveness and limitations of LPS in Egypt. The author first started by conducting a survey in order to know whether participants were aware of the LPS tool and have them rate the difficulty of implementing the system in the Egyptian market. It is important to note that the survey included participants working with contractors, consultants and developers (owners), this made the survey inclusive of all different opinions. However, the survey was done on only 22 participants and the researchers did not indicate their level of experience, this makes the data retrieved not very trustable and it affects the overall credibility of the research. The survey showed that 91% of participants were not aware of LPS and have never heard of it before. In addition, 81% of the participants viewed that the implementation of LPS was very difficult in the Egyptian market. The survey showed that the main challenges of the application of LPS in Egypt are as follows: 1) the Egyptian professional's resistance to adaptation of a new culture. 2) the complexity of the LPS technique on the workers at the site. 3) the inaccuracy of the time schedules for projects. 4) lack of awareness and commitment from stakeholders. 5) the time spent on planning is seen as a waste of time. 6) lack of communication in Egyptian sites. Looking at these challenges, one can agree with the results of this survey as the Egyptian construction is very complicated and difficult. As seen from the survey, the majority of project managers are most comfortable with the traditional construction techniques. Therefore, they will naturally resist implementing a new technique. Especially that the LPS is not easy to implement as it is complex, it involves multiple levels, it needs a deep understanding of the tool and it requires a great level of commitment.

Abdel hamid et al. (2019) then started to present proposed strategies in order to help overcome the challenges. They proposed conducting training that would get stakeholders involved in the project more familiar with LPS. Moreover, presenting case studies of successful applications of the tool as a way to convince people of the effectiveness of LPS. The proposed strategy would help raise the overall awareness of the concept of lean practices. Moreover, stressing the effectiveness of LPS on the time and cost of the project would convince stakeholders to consider change. As for the issue of lack of commitment of people, Abdel hamid et al. (2019) suggested a system of competitive partnering, which involves having two or more parties partner together for a project. Then, the parties would adopt the LPS and the project developer would provide incentives based on the better PPC performance. Abdel hamid et al. (2019) then cited a reference Nani & Apraku (2016) which found that since workers in Africa and the Middle East generally have low salaries, they rank bonuses as their number one financial reward system and that performance is boosted whenever there are financial bonuses. The author also suggested introducing the LPS system in Egypt in two phases. Where phase 1 would include implementing the LPS system on a small-scale project with a contract value less than 5 million EGP and with a repetitive nature. Where this project will initially start without implementing the LPS and then LPS tools will be introduced. Then, the different project tracking values will be compared to emphasize the effect of implementing LPS. This would then lead to phase 2 that involves integrating LPS schedules with 4D simulation for larger projects. Where a presentation will be done to familiarize people of the LPS tool and present the findings in the project of the first phase. Then, BIM technology is used to show the change in construction sequence when using LPS. During implementation, weekly tracking is conducted and analyzed to make sure that there is advancement. When analyzing this strategy, one can see that it will take a very long time to have a credible database that can be used in marketing. Moreover, the author's suggestion of using BIM models and 4D sounds convincing in theory, however the majority of construction companies in Egypt still do not use BIM. Therefore, using BIM models to market the effectiveness of LPS might make people reluctant as they would feel too unfamiliar with the process.

When comparing the findings of Salem et al. (2005) and Abdel hamid et al (2019), it is noticeable that the effectiveness of a lean construction does not rely solely on the improvement of the tool itself, it also relies on the culture that this tool would be implemented in. For example, in the case study presented by Salem, the LPS was perceived to be ready for implementation with few recommendations in the country (not mentioned) that the study was conducted in. While on the other hand, things did not look very promising in the study conducted in Egypt as the majority of people were not even aware of the technique. This indicates that the Egyptian market relies on familiar traditional construction methods and has a greater resistance to change. It also shows that greater efforts should be exerted in order to manage the implementation of lean techniques in Egypt. This can be done through simplifying the lean tools in order to appropriate them to the culture. Such appropriation would help convince people to easily transition to lean tools.

In further attempts to evaluate the effectiveness of lean construction tools, this study was conducted by Li et al. (2017), in order to assess how lean construction is implemented in

China and show what factors contribute to its implementation. The paper worked on comparing two large construction firms in China, TGC and HCG, where TGC is a state-owned company and HCG is a privately held company. 10 projects from each company were selected to be evaluated, which is good as it provides a large spectrum for evaluation. The survey was done on 7 construction management tools and the evaluation index is shown in Table 3 below. Where for every question shown in the table below, 50 workers from each company rated from 1 (lowest) to 5 (highest) their degree of agreement or disagreement with its implementation. The expertise of the survey respondents ranged from project managers, assistant managers, foremen, and workers. The results of all questions were added together and the mean was taken to give an implication about the effectiveness of each of the 7 lean tools in question. The survey results can be seen in Table 4.

Table 3: Evaluation index system of lean construction implementation (Li et al. 2017):

Last planner system (LPS)	1: Percentage of weekly plan completion
	2: First-line managers (foremen) participate in the work week plan
	3: After completion of the weekly work plan, adjust monthly plan
Visible management (VM)	1: Publish work task standard company-wide
	2: The progress, quality, and safety information company-wide posted
	3: Task commitment signed to each captain
Conference management (CM)	1: Daily meetings to discuss previous day's work and arrange work for the day
	2: First-line managers conduct weekly meeting, discuss work problems of last week to arrange work for next week
Just in time (JIT)	1: Construction process working smoothly, no waiting time, also no spare processing
	2: Constraint management of various standards and requirements during construction
	3: Material, manpower, equipment sent to the scene on time according to regulations
Concurrent engineering (CE)	1: Various assignments of construction activities and assignment flow standardization
	2: Parallel construction
	3: Construction team or group maintains information sharing
	4: Collaborative construction and design
	5: PDCA technology
Total quality management (TQM)	1: All staff participate in quality control
	2: Whole process quality control
	3: Construction cost accounting
	4: Timely maintenance and repair of equipment failure
6S On-site management	1: Classify (Seiri): Separate the waste from the required materials at this stage
	2: Tidy (Seiton): Track the position of construction tools, equipment and documents on the site
	3: Clean (Seiso): Clean the construction site to a no dirt clean condition
	4: Purify (Setketsu): Maintain the cleanliness of the construction site and standardize it
	5: Accomplishment (Shitsuke): Train employees to abide by the rules and regulations and form good civilized habits and team spirit
	6: Safety: Prevent potential accidents and eliminate dangers to ensure personal safety and production is normal

Table 4: The results of lean construction implementation (n=50) (Li et al. 2017)

Instruments of lean construction	TGC		HCG	
	Mean (m)	Standard deviation	Mean (m)	Standard deviation
LPS	3.73	0.70	4.14	0.61
VM	4.10	0.41	3.76	0.72
CM	3.64	0.52	4.00	0.61
JIT	3.67	0.54	4.01	0.50
CE	3.86	0.59	4.03	0.58
TQM	4.18	0.47	4.47	0.46
6 S	4.11	0.40	3.89	0.49
Overall	**3.90**	**0.56**	**4.04**	**0.60**

As seen in the table above, the mean values for the overall implementation of the tools for both companies are very closely tied. The author tried to understand the meaning of the survey conducted through interviews with respondents from each company. The interviews showed the difference in understanding of lean as a concept in both companies. For example, TGC views lean construction as a way to achieve green construction where they focus on reducing waste and carbon emissions. Moreover, TGC project managers showed resistance to culture change as managed projects according to the traditional ways; therefore, they do not have a clear implementation scheme of lean construction. On the other hand, HCG views lean construction as a method that helps in improving profits by optimizing the construction process, reducing material waste and avoiding delays. Though this was not clearly written in the paper, the difference in the mindset of the two companies may be the reason why the overall implementation of lean principles in HCG is higher than that of TGC. This is due to the fact that the mindset of HCG is closer to what lean construction truly is than the mindset of TGC, which makes the implementation more effective. Therefore, an important conclusion can be drawn and that is the effectiveness of lean construction is only as good as the correct understanding of lean principles. Therefore, in order to make sure companies understand lean principles correctly, professional training programs can be done to educate employees. Such training can also educate companies on the different benefits of correctly implementing lean. That way, companies are more willing to implement new techniques as they would feel more equipped and confident.

The paper also lists the factors that positively and negatively influenced both companies when applying lean construction techniques. TGC viewed that a positive factor that lean construction provides is strong organizational structure, where traditionally, actions of all employees in the project have to act in accordance with the management plan. This does not provide workers with a sense of ownership and prolongs the troubleshooting process. However, the lean technique provides the pull system, where workers are able to stay in direct contact with decision makers. This makes their voices heard and accelerates the process of rectifying any errors. The second factor that TGC viewed as an obstacle when implementing lean is the level of education and information that workers have. Where if workers do not have a proper knowledge, they will not be able to apply lean techniques and therefore the desired outcome will not be attained. Again, this enforces the importance of having a training program that educates employees prior to implementation of the techniques. As for HCG, they viewed that lean helps in providing a solution to the gap between the design stage and the construction stage. Where construction on site does not necessarily follow the exact design process due to the frequent changes in the schedule. Hence, they viewed that the pull planning technique done through LPS provided a more effective alternative to the traditional push planning technique. Another factor that HCG saw as challenging, is the material schedule planning. Where in order to correctly implement lean, materials have to arrive at site perfectly on time in order to avoid delaying work due to lack of material or overstocking of materials due to early arrival (Li et al. 2017). Overall, this paper gave a proper insight through assessing several projects in two different companies. The variability of the projects and the different identities of the companies provided more opinions and gave different perspectives as to the challenges faced by the companies when implementing lean. The only shortcoming of the paper was that the author did not explain the results found in great detail. The discussion part of the paper involved some statistical tests that were not explained and hence the significance of these tests results were not appreciated by the reader. Such explanation of the statistical tests done would have given the readers a more profound understanding of the results. It would also allow the reader to make their own assessment of the credibility of such tests and their results (Li et al. 2017).

2.4 Developing Scoring Indices

Scoring indices are usually established for the purpose of evaluating performance. They serve as early warning systems for entities to monitor their performance and set mitigation plans when their performance is hindered. The validity of a scoring system is derived directly from the legitimacy of the logic that the score is built upon (Kapliński, O., 2008). Hence, it is important to study how the different scoring indices are developed and what are the different aspects that should be considered when developing a fair scoring index

2.4.1. Scoring indices evaluating construction projects

Since the purpose of this research is to develop a project leanness score, previously established scoring systems that evaluate construction project performance were studied. Table 5 shows a compiled list of the research efforts that developed scoring systems that assess different aspects of construction projects (Elsayegh et al., 2021).

Table 5: Scoring systems developed in previous literature

Scoring Methods in previous literature	**Reference**
Pre – Construction scoring systems:	
Score to aid contractors in deciding on whether to bid or not in new projects	(Chisala, 2017)
Score to measure accuracy of the estimated project cost – Estimate Score Program (ESP)	(Oberlender et al., 2021)
Score measuring the project's construction readiness – Construction Readiness Score (CRS)	(Ibrahim et al., 2021)
Index indicating how well the project's scope is defined in the detailed design phase before construction	(Dumont et al., 1997)
Project Management:	
Evaluation of benefits associated with implementing information systems in construction management process	(Yu et al., 2006)
Score assessing contractor's overall performance – Project Quarterback Rating (PQR)	(Hanna et al., 2014)
Rating system assessing competencies of project managers	(Hanna et al., 2016)
Rating score that assesses project sensitivity to the risk out-of-sequence events as compared to the averages of such risks in the industry.	(Abotaleb et al., 2020)
Index assessing the effectiveness of collaborative planning in construction - Collaborative Planning Index (CPI)	(Elsayegh et al., 2021)
Performance Indicators:	
Rating system to assess the possible positive outcomes of implementing a technology on construction productivity	(Goodrum et al., 2011)
Model assessing performance for water and wastewater construction projects – Project Performance Rating (PPR)	(Abi Shadid et al., 2019)
Index evaluating globalizing performance of construction and engineering firms	(Comu et al., 2015)
Guiding model measuring maturity of integrated industrial project delivery capabilities	(Barutha, 2018)
Score measuring integrated project delivery enhancement through implementing information and communication technology	(Ahmad et al., 2019)
Benchmarking labor productivity through indices like the disruption index (DI), performance ratio (PR), and project management index (PMI)	(Abdel-Razek, et al., 2007)
Sustainability Ratings:	
Rating system for assessing sustainability rating systems – Meta framework Assessing Ratings of Sustainability (MARS)	(Papajohn et al., 2017)

2.4.2. Lean Construction Rating System

The available literature is very limited when it comes to developing scores assessing the leanness of construction projects. This may be due to the fact that implementing lean tools in a construction project does not in and of itself suffice for the complete “leanness” of the project. Therefore, evaluation of the leanness of a project is complicated as it has to include several aspects. The only study that is found to develop a leanness rating is this research that was conducted in a team effort done between the University of Karlsruhe in Germany and the Universidade Federal do Parana in Brazil. Where the primary objective of the research is to assess the applications of lean construction in Germany and Brazil. The quality rating model depends mainly on performing qualitative analysis through conducting interviews and a quantitative evaluation that shows the degree of applying lean construction in projects (Hofacker et al. 2008).

The process of obtaining a quality rating is done through four main processes: 1) brainstorming and mind mapping 2) Evaluation sheet 3) visualization of results and 4) categorization into degree of company leanness. In the brainstorming phase, the model incorporates two different framework models, the rapid plant assessment and the model for evaluating the degree of leanness of manufacturing firms. It also incorporates a detailed questionnaire comprised of 30 questions for 6 main categories. These categories are: 1) client focus, 2) waste consciousness 3) quality 4) material flow 5) organization, planning & information flow 6) continuous improvement (Hofacker et al. 2008).

In the evaluation sheet, each of the 30 questions are given ratings from 0 to 6 where 0 means not applied and 6 means fully applied. Based on the responses of the questionnaire, a percentage of each category is graphed in order to show areas of strength and highlight areas of weakness. An example of this graph is shown in the Figure 2 below. Then, the percentage of all 6 categories are added together and divided by 180 (the total points for the 30 questions) and a classification of the leanness degree is obtained through the scale shown in Figure 3 below. The quality rating model then classifies companies into three main classes. Where companies in the “A class” are applying lean construction principles perfectly, “B class” are companies that focus on achieving high quality and are exerting efforts to implement lean construction philosophy. As for “C class” companies, they are conscious of quality but they have very low awareness of lean philosophy. Lastly, “D class” companies have very low quality and have wastes (Hofacker et al. 2008). This paper presents a very useful scoring scale however, one of its biggest shortcomings is that it does not provide areas of strength and weakness to the companies who participated in the research. Therefore, the scale is not very beneficial if it is not accompanied with proper insights and action points for the companies to further improve their lean performance. There are no other papers found that gave insights on what companies should do to improve performance. Hence, such evaluation system along with insight and points of improvement could be expanded on in this research.

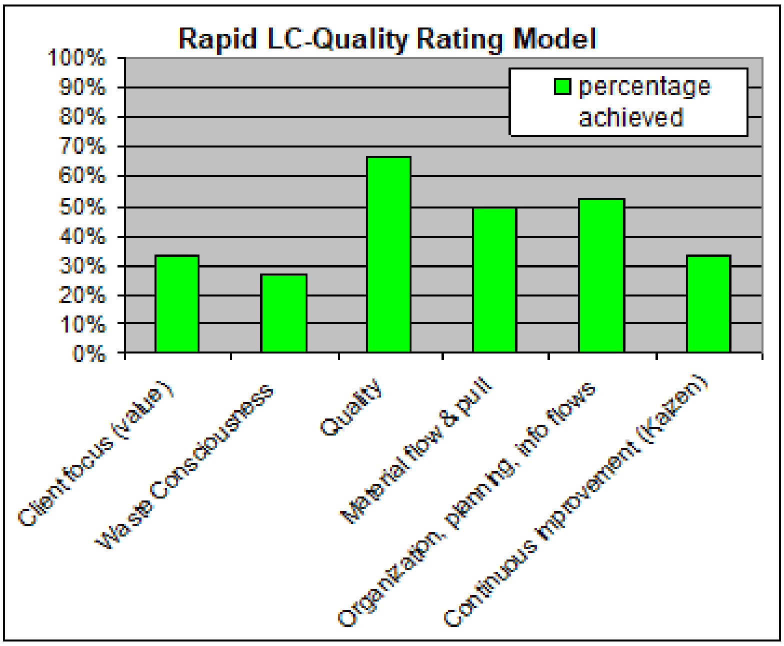


Figure 2: Rapid LC-Quality Rating Model (Hofacker et al. 2008)

	Result	% achieved	step	Interpretation of class
LC	aaa	95% to 100%	6	(strive for perfection in quality improvements and LC application)
LC	aa	89% to 94%	6	
LC	a	81% to 88%	8	
LC	bbb	73% to 80%	8	(high quality focus and lean-learning within the main project / company levels)
LC	bb	64% to 72%	9	
LC	b	55% to 63%	9	
LC	ccc	46% to 54%	9	(quality consciousness, but low/no lean-construction knowledge)
LC	cc	37% to 45%	9	
LC	c	28% to 36%	9	
LC	ddd	19% to 27%	9	(low quality and low improvement focus, wasteful)
LC	dd	10% to 18%	9	
LC	d	0 to 9%	10	

Figure 3: Quality rating scale (Hofacker et al. 2008)

2.5 Problem Statement

As seen, there are several factors in a project that are directly affected by the implementation of lean principles. These factors can be technically related to the project, such as improving quality, material flow & pull, schedule and cost overruns and efficiency of equipment & resources used. Lean principles also improve the project on the managerial level through improving client focus, waste consciousness. organization planning & information flow, continuous improvement and lastly coordination among parties. In conclusion, the literature found on lean construction is very rich when it comes to explaining the different lean techniques and tools. There are also several studies that address the effectiveness of lean tools when implemented in construction sites. However, very few research efforts could be found on evaluating the implementation of lean principles in construction sites. Consequently, there is a knowledge gap on how to give advice companies on areas to improve based on their current lean practice positions. For instance, the quality rating model presented by Hofacker (2008) has limitations as it only indicates to companies where they stand but does not indicate areas for improvement nor does it provide a benchmark for companies to compare their performance to others. Therefore, there is no real benefit for a company to know where it stands on the scale if it is not provided with insights on how to move up the scale. Knowing the factors in construction projects that are directly affected by lean principles, they can be used to give a complete assessment of a company’s performance. Moreover, the effect of implementing lean principles on project performance can be used to predict the project’s performance in terms of schedule and budget. In other words, just by implementing lean construction tools does not guarantee reduction in cost and time overruns. There is a gap when it comes to identifying the factors that support the success/failure of implementing lean construction tools, and quantifying the impact of those factors to the actual performance of construction projects. Hence, this is the gap that this study intends to fill, where it will provide a project leanness score and benchmarking scale that show where a company stands and where it needs to improve its position based on other companies in the industry.

Chapter 3. Research Methodology

The methodology proposed in this chapter follows seven different stages with different tools for each stage. Based on the literature review presented in the previous chapter, a conclusion can be drawn that there are several factors affected by the implementation of lean principles. Therefore, in order to be able to develop an accurate leanness score, data is collected through surveys that tackle two different aspects. The first, expert-based surveys, where experts who have previous experience with lean construction answer a survey to help determine the key factors that are directly affected by implementing lean construction. Then, a project-based survey is conducted in order to be able to assess the performance of construction companies. Performance assessment is done based on the key factors obtained through the expert surveys. Based on the results of both surveys and the literature analysis, a project leanness score and benchmarking scale are developed in order to quantify the overall quality of performance of the company and highlight points of strength and weakness. The sequence of the methodology is shown in Figure 4 below:

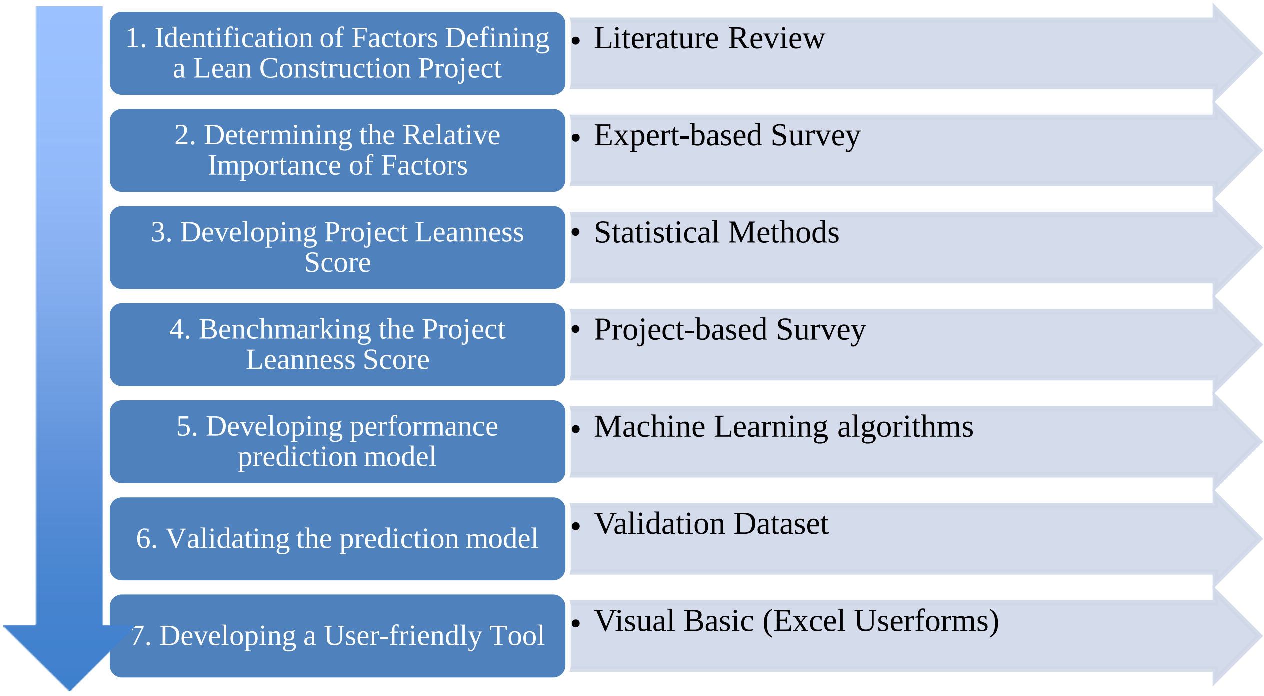


Figure 4: Sequence of methodology

3.1 Identification of Factors Defining a Lean Construction Project

In the kickoff stage of this research, literature review analysis is done in order to be able to find out which lean factors directly affect construction projects the most. This stage is critical as the lean factors identified in this stage are used as basis to build the survey questions and the evaluation model in the stages to follow. Hence, extensive literature review research is done and as soon as the lean factors are identified, the second stage of the research begins.

3.2 Determining the Relative Importance of Factors

This stage of the research involves creating an expert-based survey. Where a questionnaire is generated and responses of experts who previously worked utilizing lean Principles is collected. The questions in this survey are based on the factors identified in the first stage of the research. As previously mentioned in Chapter 2, such factors can include: client focus, waste consciousness, quality, cost and time overrun. The main aim of the expert-based survey is to be able to assign weights to each of these factors based on the expert opinions gathered. These weights would then dictate the relative importance of each of the factors. The relative importance of factors is beneficial when developing the project leanness score as it helps treat each factor according to the weight of its importance. For example, if the majority of experts agree that a certain factor rarely affects project performance, then it will not significantly affect the performance assessment of the company. Consequently, it will make a low impact on the score calculation leading to a more accurate scoring system.

3.3 Developing Project Leanness Score

The third stage of the research involves developing a project leanness score based on the responses retrieved in the expert-based survey. A database is created based on the responses collected and is used in order to apply statistical analysis. Such statistical analysis indicates which lean factors most directly affect construction projects. Hence, directing the emphasis of research to the factors that are important to focus on in later stages. Moreover, it also dictates that these lean factors need to be assigned higher weights in the project leanness score. By assigning factors different weights depending on their relative importance, one can ensure that the project leanness score accurately and realistically assesses companies' performance.

3.4 Benchmarking the Performance Score

Benchmarking is a comparative method that is used in the process of establishing an indicator that compares measured performance against practices in a certain field (Chandra, 2020). In this stage, a project-based survey is created. This survey targets as many construction companies as possible and they are asked to fill out questions related to their project performance. The data is collected directly from the teams working on the projects in order to ensure its credibility. Responses are then used to evaluate the overall performance of the company based on the project leanness score developed in the previous stage. The resulting scores of the participating companies give an insight on the construction industry's overall quality and frequency of implementing lean principles. Having such database provides an overview on the industry's general performance. Where patterns in the industry's performance are identified through statistical methods and a project leanness benchmarking scale is established based on these patterns. The project leanness score together with the project leanness benchmark scale offer a holistic evaluation of companies' performance. Where companies would be able to know their scores which represent the overall rate of implementing lean principles in projects and would also be able to compare their performance to other companies in the industry based on the project leanness benchmarking scale.

3.5 Developing Performance Prediction Model

3.5.1. Background About Machine Learning techniques

Machine learning is a type of artificial intelligence that enables software applications to predict results accurately relying mainly on training algorithms that do not depend on explicit programming (Mitchell, 1997). This is done through using historical data as input to predict new output values. Machine learning is beneficial when solving complex prediction problems where the input data are complicated and do not have a clearly identifiable trend (Harrington, 2012). The reason being that the algorithms are trained to simulate human intelligence in learning the data. This is done through well established and extensively researched learning tasks that include, but are not limited to, classification, regression, ranking and clustering (Mohri et al. 2018). Where classification assigns pre-defined categories to each data item; it can be applied to any dataset that can be categorized into a finite number of categories. This can help in classifying things like documents, where machine learning algorithms classify them based on their topics (i.e.: sports, business, economics etc.). Regression tasks predict a numerical value for each item in the dataset based on predictor variables. The validity of regression models depends on the difference between actual and predicted values. That said, machine learning algorithms can perform linear and non-linear regression depending on the trend between the dependent and independent variables. Ranking orders the data set based on an established standard; a famous example of this task is ranking web pages for a search query from most relevant to least relevant. Lastly, clustering which partitions items into homogeneous regions. It is best used to analyze large data sets where data is divided based on a certain behavioral pattern. An example of that is social network analysis where algorithms attempt to identify communities (clusters) within large groups of people (Mohri et al. 2018).

Machine learning algorithms are able to perform the above-mentioned learning tasks through learning scenarios, these scenarios vary based on the type of input data. There are three main types of learning scenarios; supervised learning, unsupervised learning and semi supervised learning (Sathya et al. 2013). Supervised learning is used when there is a set of pre-labeled examples available for use as training data. The model then learns the labeled data and makes predictions for the unlabeled data or, in other words, test data. This scenario is most commonly used in classification, regression, and ranking problems. On the other hand, the unsupervised learning scenario studies unclassified data and makes predictions based on trends in the data. This method is used in clustering problems. It should be noted that there is a limitation to unsupervised learning as the precision of the model cannot be accurately measured to evaluate its performance. The semi-supervised learning scenario acts as the middle ground between the supervised and the unsupervised learning. Where the data consist of labeled and unlabeled data, and the model makes predictions for the unlabeled data. Semi supervised learning is useful in cases where unlabeled data are available but labeled data are rare or not easy to find (Sathya et al. 2013).

Each learning scenario is employed using certain techniques and algorithms. For example, linear regression, uses the slope formula to model the relationship between two or more variables. As seen in Figure 5, the linear regression equation depends on two main input variables, the dependent and independent variables. Where the independent variable is independent of other variables, and the dependent variable is the effect that is directly affected by the independent variable. Linear regression is best used when there is a linear relationship between the independent and the dependent variables. Among the advantages of using regression in a predictive model is that its algorithm is very simple to implement and interpret. However, it is important to note that the legitimacy of predictions using linear regression depends greatly on the quality and quantity of the data. This means that if the data has outliers, this will have a great impact on the regression and may lead to the model over-fitting (Schneider et al. 2010). The precision of the regression model depends on the calculated adjusted R^2 value of the model. The adjusted R^2 value, referred to as the correlation coefficient, represents the correlation between the dependent and independent variables (Schneider et al. 2010). The adjusted R^2 is a statistical measure that gives an indication on how much variation in the dependent variable of the model is explained by the independent variable (Schneider et al. 2010). The adjusted R^2value is a number between zero and one, he closer the adjusted R^2 value is to one, the higher the correlation between the variables, and therefore the more precise the predictive model will be (Schneider et al. 2010).

Constant/Intercept Independent Variable

$$Y_i = \beta_0 + \beta_1 X_i$$

Dependent Variable Slope/Coefficient

Figure 5: Linear regression equation (Schneider et al. 2010)

Supervised learning techniques, such as decision trees and neural networks, were studied for the purpose of this research. Simply explained, a decision tree is a diagram that helps define a course of action by displaying its statistical probability (Quinlan, 1986). The typical structure of a decision tree is shown in Figure 6; it consists of two elements, nodes and branches. Where nodes represent decisions and branches represent the possible events that can happen based on the decision. The most distant branches of the tree represent the end result of a given decision path and they are referred to as end nodes or leaves.

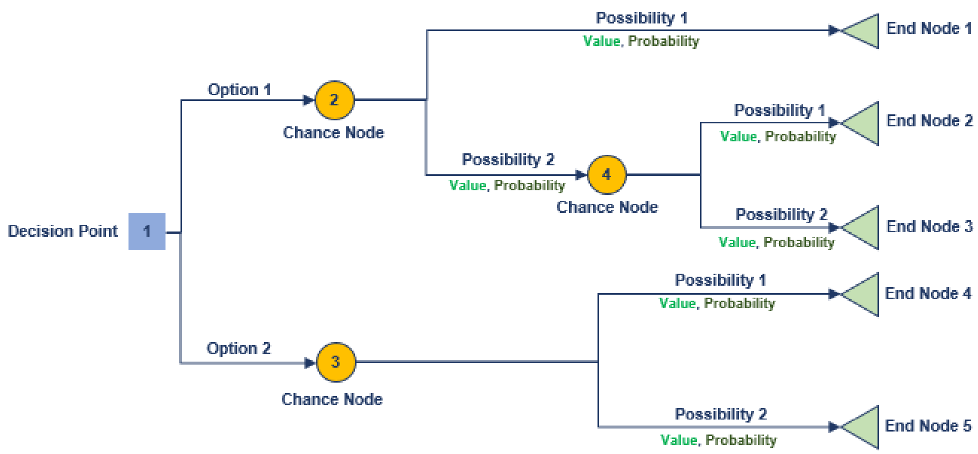


Figure 6: Decision tree structure (Magnimetrics, 2021)

There are two main types of decision trees, continuous variable decision trees and categorical variable decision trees; these types work best with non-linear data. Continuous variable decision trees are used when there is a continuous target variable. For example, predicting income range based on continuous input variables such as age, gender, profession and others. Categorical variable decision trees, also referred to as classifier decision trees, are used when the end target is classified into known categories. In that case, there is only one outcome and its either true or false based on the pre-defined categories (Quinlan, 1986).

Another supervised learning technique is neural networks; where algorithms are built to simulate the structure of the human brain (Moselhi et al. 1991). These algorithms take in data, train themselves to recognize a pattern within these data and predict the output for a new set of similar data. The structure of a neural network consists of layers made up of several neurons or nodes. The first layer is typically the input layer, where it receives input data. Then, hidden layer(s) exist where their main function is to compute the network analysis. Lastly, the output layer predicts the final output. Neural networks are computed through an iterative process were information travel in forward and backward propagations (Moselhi et al. 1991). This process, as outlined in Figure 7, allows the neural network to train on the input data, predict the outcomes and compare prediction values with actual values; then, the outcome results are fed back to the network where another iteration is performed. This iterative process is repeated until the network converges to the least error.

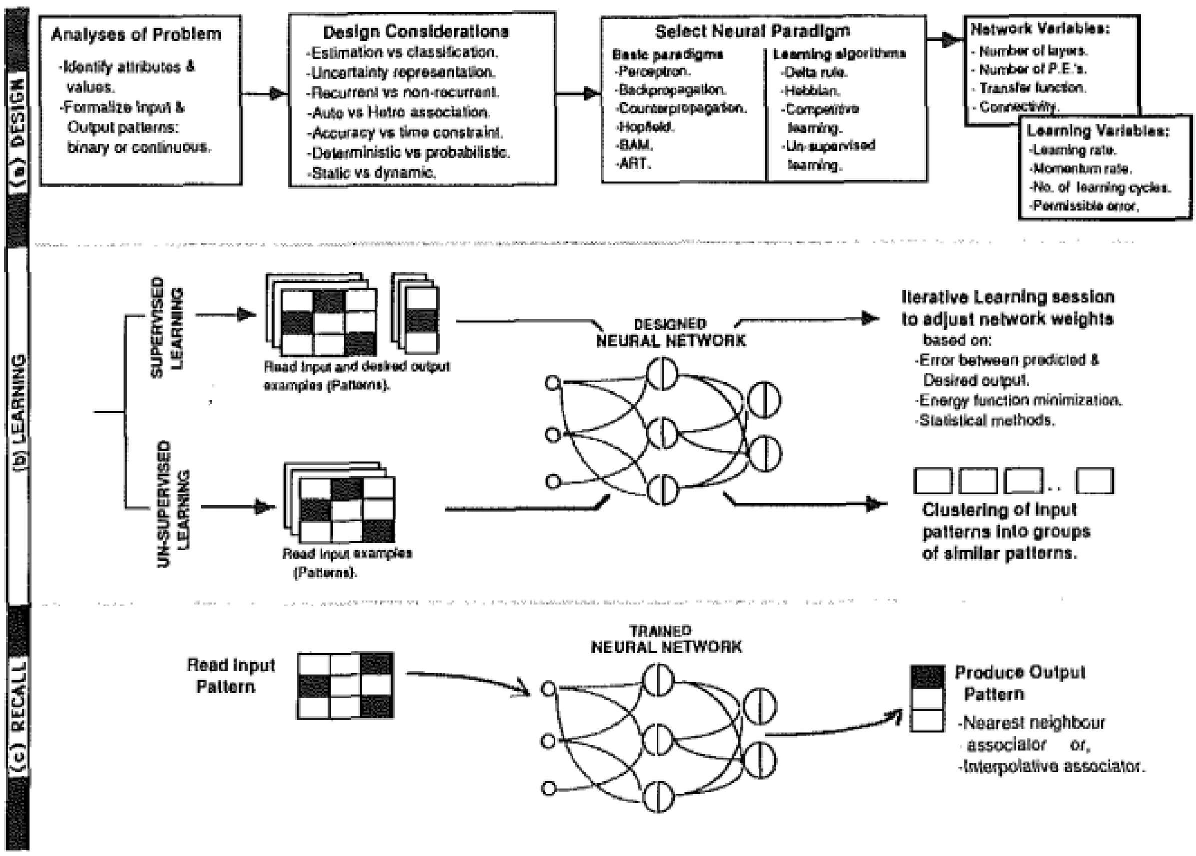


Figure 7: Development cycle of a neural network (Moselhi et al. 1991)

The output of neurons in a neural network depends on their activation function. These are threshold functions that define the output of the neuron given a set of inputs. The most commonly used activation functions are logistic sigmoid, hyperbolic tangent (Tanh) and rectified linear activation (ReLU) (Sibi et al. 2013). The logistic sigmoid function takes input values and transfers them to a range of values that are between zero and one. The more negative the number is, the closer the output value will be to zero and vice versa for positive numbers. A value of zero represents an inactivated neuron and the value of one represents an activated neuron. The reason for such transformation is to trigger certain actions within the neural network where the outcome of the network is dictated based on these actions (Sibi et al. 2013) The Tanh function is similar to the sigmoid function; however, it transforms values to a range between -1 and 1 following the same reasoning as the one used in the sigmoid function. Not all activation functions take input values and transform them to a pre-defined range. In fact, the ReLU function takes input values and converts them to a maximum of either zero or the value of the input itself; where the more positive the neuron, the more activated it is (Sibi et al. 2013). It should be noted that the better the accuracy that the activation function yields, the more suitable it is for use in the model.

3.5.2. Previous Use of Machine Learning in the Construction Industry

Machine learning techniques have been utilized several times in applications relating to the construction industry. For example, Gondia et al. (2020) utilized categorical decision trees in building a model that predicts projects' delay through performing a project delay risk analysis. In addition, continuous variable decision trees were used by Desai and Joshi (2010) to predict construction labor productivity rates based on the project's surrounding area, location, temperature and labor's age group. Neural networks were also utilized in several construction related applications. In an extensive literature review, Doroshenko (2020) exhibited some cases where neural networks were applied in the construction industry. For example, they are implemented in tasks related to energy consumption of buildings. Where the network is used to predict the heating and cooling system load through the energy consumption of the building. Moreover, it studies the thermal insulation properties of the materials used in the building walls; giving an analysis of the building's energy consumption. Neural networks were also utilized in a model that was developed to predict construction material prices in a given month based on input data that consisted of the material prices of the previous month along with the average prices of the preceding year (Marzouk et al. 2013). Lastly, Elsayegh et al. (2021) used neural networks and support vector machines as predictive algorithms to develop a collaborative planning index.

3.5.3. Application

In light of the background discussed, the validity and rationality of having an accurate prediction model depends on two main things, strong data acquisition and adequate data analysis. The particular reason for that is that the stronger the database that the model is built upon, the more efficient and consistent it becomes. This stage involves utilizing different machine learning techniques to train the evaluation model to predict project's schedule and budget performance based on their implementation of lean factors. Using the project-based survey, correlations between lean factors implementation and budget and schedule underrun or overrun are made. This is done through trying several computational machine learning techniques for the purpose of building an accurate prediction model. The different machine learning techniques tried are linear regression, non-linear regression, decision trees and neural networks. The models' input variables are the lean factors' scores computed through the established scoring system while the models' output variables are set to be the predicted schedule and budget performance. The output variables' form varied once having a numeric representation and another time having a categorical classification. The algorithm that is able to accurately find trends in the data and correlates these trends to the project's schedule and budget performance is chosen. Consequently, developing a predictive model that is able to predict the project's schedule and budget performance based on the company's implementation of lean principles.

3.6 Validating the Prediction Model

In order to be confident in the legitimacy of the algorithm of the predictive model, a validation dataset is used to test it. This validation set consists of testing data that was not used when training the model in addition to hypothetical data representing extreme cases. The main aim of using the testing data is to validate that when new data is entered the model gives realistic predictions of project performance.

3.7 Developing a User-friendly Tool

A user-friendly tool is developed in order to display the outcomes of the company's assessment in a simple manner that is beneficial and informative to companies. The outcomes consist of the total score displayed on the project leanness benchmarking scale and a set of performance indicative charts. These charts show the stance of the company's performance as compared to other companies in the database. This way, the model not only gives the user their score, but also provides them with a broader understanding of their performance as compared to other companies. Consequently, providing possible redirection of companies' way forward action plans based on how other companies are performing.

Chapter 4. Development of the Project Leanness Score

4.1 Identification of Factors Defining a Lean Construction Project

The first step in order to develop an evaluation model that fairly assesses companies' performance is to identify the most influential factors that affect construction projects. Such proper identification of these factors would allow the evaluation model to accurately assess the performance of a company based on the factors that, if present in a construction project, enhance the overall efficiency, morale, quality and several other aspects. It is important to identify such factors as it would ensure that the evaluation is being done based on realistic factors that can be applied in real life. The identification of these factors was achieved through an extensive literature review. The sources found provide an overview on the factors that are likely to be directly affected by the implementation of lean principles. For example, Hofacker et al. (2008) highlighted through their research that lean construction principles enhance client focus, improve communication between the key stakeholders of the project, improve the overall quality, provide for a better organization and information flow and provide room for continuous improvement (Hofacker et al. 2008). When looking at the factors mentioned in this paper, one can make a positive correlation between them and the core target of lean principles. This target includes working on systematically and effectively eliminating non-value adding activities; thus, setting a strict process that does not leave room for straying away from the nominal goal of the project. Hence, improving factors like client focus which creates a good relationship between the project parties and opens room for future collaborations. Improved client focus also comes as a direct result from improved communication between parties as discussed by Hofacker. This is due to the fact that lean construction techniques force people to adequately communicate consistently, allowing critical information to be known at the right time. This regulated communication is facilitated through daily huddle meetings and lookahead meetings. Such meetings allow for the key stakeholders to develop a relationship of trust, confidence and respect and provides early involvement of key stakeholders, which, in return, ensures there is a collective input on the project's plan, schedule and risk management. The improved overall quality, better organization and information flow, also comes naturally given the effective communication from within the same party and between the different parties. This allows for a better organizational structure, which eases information flow creating an efficient decision-making process, forming ownership over the project and effectively sharing lessons learned. All these initiatives encourage people to demonstrate continuous improvement whether through showing improved behavior or through innovating an improved work process, structure or technique.

Other factors were considered in another research paper conducted on construction projects in Egypt and it included coordination among parties, meeting schedule and budget targets and efficiency of equipment and resources used (Hamed, 2013). Construction projects are complex as they include several disciplines and activities that need to be integrated together. In order to fully integrate all disciplines, a high level of coordination needs to be implemented. Such coordination should be present between the different disciplines during the design stages, the different parties during the construction stage (contractor, subcontractor, consultant and employer) and between third parties such as material suppliers etc. Lean techniques facilitate such coordination through tools like the Last Planner System which creates a harmony between the different disciplines through pull planning and also helps in detecting design miscoordination at early stages. Another tool that helps in the overall project coordination is the Just-In-Time tool which helps in developing a precise procurement plan for the project and thus creating a smooth work process, eliminating overstocking and avoiding lost time due to unavailability of material. According to Hamed, effectively implementing lean techniques also helps in meeting project schedule and budget targets. This is due to the positive attributes that lean techniques, like the Last Planner System and Just In Time, contribute to minimizing overspending on unneeded materials and storage space, getting better deals when procuring large amounts of the same materials and reducing cost through value engineering. All these aspects, when monitored through a schedule control tool like primavera and checked regularly through schedule and cost accomplishment indicators like SPI and CPI, help in providing a mitigation plan for when there is slippage leading to the project meeting the schedule and budget target. Lastly, the paper mentioned that lean techniques contribute to the efficiency of equipment and resources. This is achieved through developing a site layout that minimizes transportation, unnecessary labor and equipment movement and strategic location of the needed facilities. Moreover, lean techniques include making sure human resources are located in positions where they can best exploit their technical skills, show leadership and commitment initiatives and demonstrate innovation. This can also be aided through workshops and trainings provided by the companies in order to enhance the overall staff efficiency.

Research by El-adaway et al. (2021) considered factors like design flexibility and facilitated contractual risks and disputes to strongly influence construction projects performance. Flexibility of design allows for less disruption caused by design stages. This can help expedite the process of issuing shop drawings, procuring materials and facilitating the process of a change request or variation order. That said, balancing contractual risks in a project helps improve the overall project management. That way, the risk is not borne by one party leading to a raise in contingency and increasing chances of delays. If the contractual obligations are balanced, this will improve the project parties' relationship, decrease chances of disputes and create trust, confidence and respect.

As a result of a collaborative research effort between the University of Missouri for Science and Technology and The American University in Cairo, an extensive literature review was conducted to compile the aforementioned factors into a list and categorize them into six main categories. These categories are behavioral, communication, team, managerial, technological and contractual. Then, each of the factors was assigned to a category that relates to its topic resulting in a list of 27 factors that affect a construction project as seen in Table 6. It is worth mentioning that one cannot safely assume that the below factors are all equally important and influential to a construction project. Hence, in order to further assure that the evaluation model is precise, the factors were verified and weighted to know their relative importance through taking experts' opinions.

Table 6: List of factors that affect the performance of a construction project

Category	Factor for Successful Implementation of Lean Tools	Reference
A. Behavioral Category	A1. Adaptation or resistance to change	(Hamzeh et al. 2015)
	A2. Leadership and commitment	(Mohan, S.B et al., 2005)
	A3. Continuous improvement	(Salem, O. et al., 2005)
	A4. Trust, confidence and respect	(Ballard, G. et al., 1999)
B. Communication Category	B1. Frequency of meetings	(Poppendieck, M., 2011)
	B2. Sharing of lessons learned	(Farrar, J.M et al., 2006)
	B3. Early involvement of key stakeholders	(El-adaway et al. 2021)
	B4. Collective input in schedule development	(Abbasian-Hosseini, S. A et al., 2014)
C. Team category	C1. Team motivation and incentives	(Albalkhy, W et al., 2021)
	C2. Orientation/workshops and training/education	(El-adaway et al. 2021)
	C3. Project parties relationship	(Ballard, G. et al., 1999)
	C4. Competence of team	(Ballard, G. et al., 1999)
	C5. Sharing values and culture in team	(El-adaway et al. 2021)
	C6. Encouraging creativity and innovation	(Denerolle, S., 2018).
	C7. Team involvement and building	(Albalkhy, W et al., 2021)
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	(H. Erol et al., 2017)
	D2. Value Engineering awareness and frequency of implementation	(Chien-Ho Ko et al., 2010)
	D3. Risk Management awareness and frequency of implementation	(El-adaway et al. 2021)
	D4. Accuracy of schedule accomplishment indicators (SPI)	(Abdel Hamid et al., 2017)
	D5. Client focus	(Denerolle, S., 2018).
	D6. Problem solving and decision making	(El-adaway et al. 2021)
	D7. Flexibility of design	(Nani, G.,2016)
E. Technological Category	E1. Use of BIM	(Salem, O. et al., 2005)
	E2. Effectiveness of using a scheduling tool	(Farrar, J.M et al., 2006)
F. Contractual Category	F1. Procurement Plan	(El-Sawalhi et al., 2016)
	F2. Appropriateness of project delivery method	(El-adaway et al. 2021)
	F3. Risk balance in contractual obligations	(Poppendieck, M., 2011)

4.2 Determining the Relative Importance of Factors

After identifying the factors, an expert-based survey was conducted for two main objectives, the first is to validate the choice of the factors and the second is to rate each factor in terms of its real-life applicability and overall significance in construction projects. The results of this survey then determined the weight of each factor. This weight indicates the relative importance of each of the 27 factors to the overall success of construction projects. Assigning such weights to each factor ensures that the scoring model is not treating all factors with equal importance. By doing that, the scoring model delivers a balanced output that fairly and accurately assesses the companies' performance in the project.

The expert-based survey comprised of questions targeting the 27 identified factors listed in Table 6. For each factor, every expert had to rate its importance in a construction project based on the Likert scale shown in Table 7. From the ratings provided, the relative importance of each factor within a category could be identified.

Table 7: Expert-based survey Likert scale

Lean factors importance in a construction project	Likert scale
Not at all important	1
Low importance	2
Neutral	3
Important	4
Very important	5

In order to be able to reach the maximum number of people, the survey was distributed among connections who work in the construction industry in the USA and in Egypt. A link of the survey was posted on several professional groups on websites like LinkedIn in order to boost the reach of the survey beyond the circle of personal connections. The survey got a total of 71 responses, 53 of them were from American experts and 18 from Egyptian experts. The steps taken to assure that the survey data can be used as a reliable source to conduct the research were as follows. First, a quick check was done so as to make sure that the survey reached experts who represent the opinions of the three main parties to a construction project (consultants, contractors and employers). This is important because having input from the three parties contributes to the impartiality of the data collected. Indeed, the survey received responses from a total of 51 experts who work for contractors, 13 experts who work for consultants and 7 experts who work for employers. The below Figure 8 and Figure 9 demonstrate the category of respondents' distribution percentage of the American and Egyptian experts respectively.

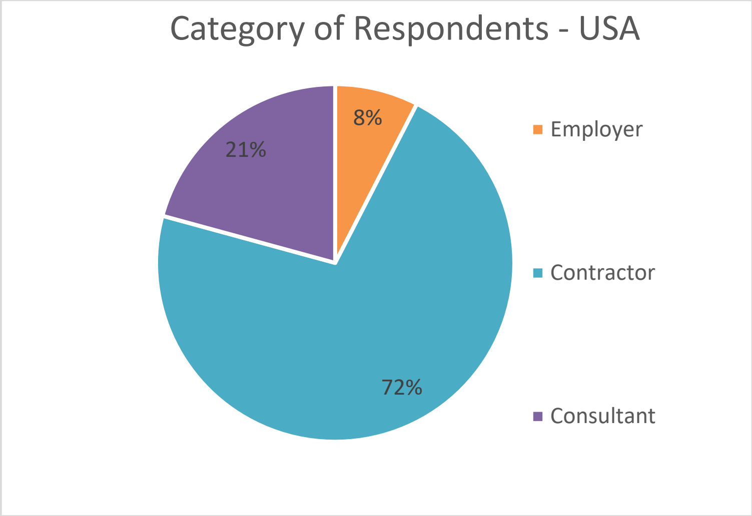


Figure 8: Category of Respondents distribution for American experts

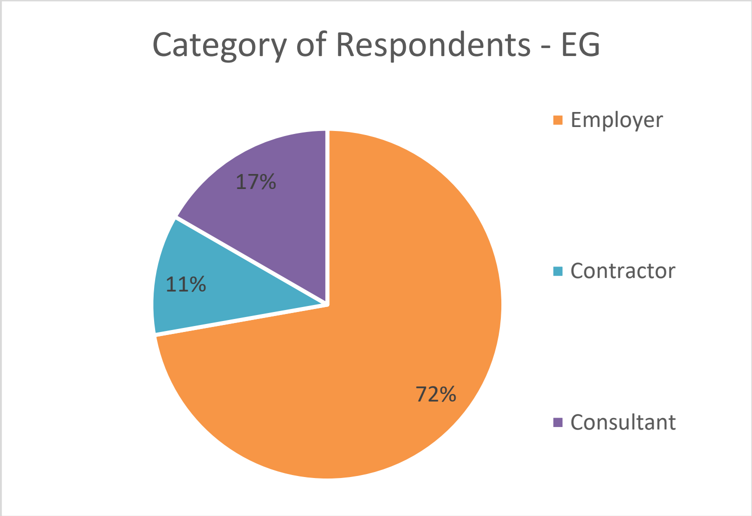


Figure 9: Category of Respondents distribution for Egyptian experts

The second check was done in order to validate that the people who took the survey have adequate years of experience that would authenticate their opinions. According to the Cambridge Handbook on Expertise and Expert Knowledge, a person is considered an expert in most fields after 10 years of experience (Ericsson et al. 2006). The average years of experience of the 53 American experts who took the survey was 25 years, while the average years of experience of the 18 Egyptians who took the survey was 9 years. Figure 10 below shows a box plot of how the years of experience of the survey respondents is dispersed. Since the average years of experience of the 71 respondents was 21 years, which is well above 10 years, the opinions expressed in the survey can be considered a dependable source to rely on. The last check performed was the Cronbach's Alpha Reliability Test, which is a statistical test that is performed in order to measure a survey's internal consistency especially when using a Likert scale. In other words, this test measures if the questions in the survey are reliably measured and whether or not people had the same understanding of the questions when answering them. This measure is done through the Cronbach's alpha value, which is calculated using Equation 1 where K is the total number of questions in the survey, Vi is the sum of variance in each question and V_t is the sum of variance of all questions (El-adaway et al. 2021). According to Tavakol et al. (2011) a Cronbach's alpha value above 0.7 is acceptable as it represents a reliable questionnaire that can be used. When calculated, as seen in Table 8, the Cronbach test for the expert-based survey gave an alpha value of 0.94 which meant that the survey is valid and that the data retrieved were suitable to be used in this research.

Equation 1: Cronbach's alpha value

$$\alpha = \frac{k}{k-1} * (\frac{1-\sum Vi}{\sum V_t}) = \frac{27}{27-1} * \left(\frac{1-23.6}{238.8}\right) = 0.94$$

Table 8: Cronbach alpha value calculations

	Factors:	Sum of Variance of each question (V_i)	Sum of Variance of all questions (V_t)
A. Behavioral Category	A1. Adaptation or resistance to change	0.87	72
	A2. Leadership and commitment	1.2	66
	A3. Continuous improvement	0.9	66
	A4. Trust, confidence and respect	0.8	64
B. Communication Category	B1. Frequency of meetings	2.1	69
	B2. Sharing of lessons learned	0.5	72
	B3. Early involvement of key stakeholders	0.7	55
	B4. Collective input in schedule development	1.8	60
C. Team category	C1. Team motivation and incentives	0.83	66
	C2. Orientation/workshops and training/education	0.73	70
	C3. Project parties relationship	0.61	70
	C4. Competence of team	0.89	61
	C5. Sharing values and culture in team	0.84	20
	C6. Encouraging creativity and innovation	1	20
	C7. Team involvement and building	0.39	70
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	1.4	74
	D2. Value Engineering awareness and frequency of implementation	0.45	70
	D3. Risk Management awareness and frequency of implementation	0.67	66
	D4. Accuracy of schedule accomplishment indicators (SPI)	0.61	72

	D5. Client focus	0.7	66
	D6. Problem solving and decision making	0.89	66
	D7. Flexibility of design	0.71	64
E. Technological Category	E1. Use of BIM	0.61	69
	E2. Effectiveness of using a scheduling tool	0.83	72
F. Contractual Category	F1. Procurement Plan	0.67	55
	F2. Appropriateness of project delivery method	0.91	60
	F3. Risk balance in contractual obligations	1	66
Total		23.6	238.8

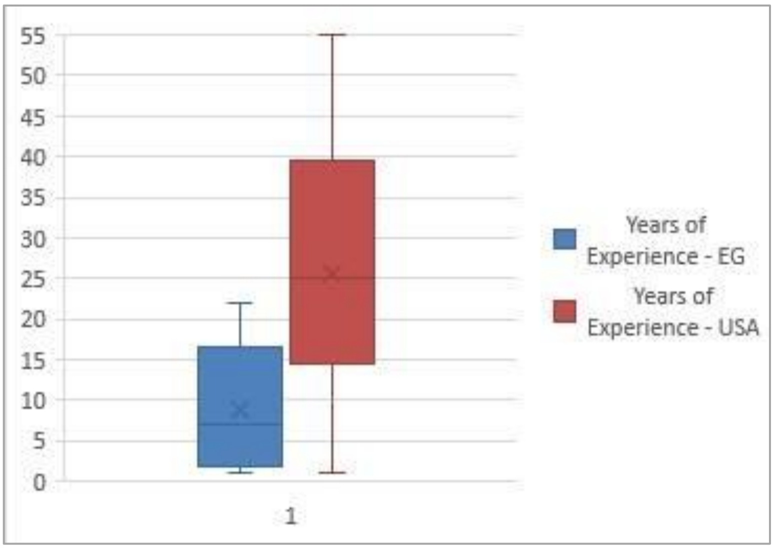


Figure 10: Box Plot demonstrating variation in years of experience

After validating the survey, the following steps were taken in order to determine the relative importance of each of the identified factors. First, the responses from the American experts were separated from the responses of the Egyptian experts. This was done in order to observe if there is a significant difference between experts' opinions who work on projects in the USA vs. expert's opinions who work on projects in Egypt. Then, expert ratings for the importance of each factor were listed and the average result of the responses received for each factor was taken as shown in Table 9. It is worth mentioning that the number of Americans who took the survey was almost three times the number of Egyptians. Hence, when comparing the factor averages presented in Table 9, it can be observed that the factor average for Egypt is generally higher than the factor average for USA. This is due to the variance in the sample size; USA being triple the sample size of Egypt. Therefore, when analyzing the data, one cannot simply draw a conclusion if opinions on the significance of a factor varied between the two countries just by comparing the average response for each factor as this would not be indicative.

Table 9: Average factor ratings in USA and Egypt

	Factors:	**Factor average (USA)**	**Factor average (EG)**
A. Behavioral Category	A1. Adaptation or resistance to change	2.85	3.72
	A2. Leadership and commitment	3.00	4.22
	A3. Continuous improvement	2.82	3.89
	A4. Trust, confidence and respect	3.07	4.17
	Sum Category A	**11.74**	**16.00**
B. Communication Category	B1. Frequency of meetings	2.56	3.28
	B2. Sharing of lessons learned	2.89	3.94
	B3. Early involvement of key stakeholders	3.08	4.00
	B4. Collective input in schedule development	2.79	3.67
	Sum Category B	**11.32**	**14.89**
C. Team category	C1. Team motivation and incentives	2.85	4.28
	C2. Orientation/workshops and training/education	2.49	3.72
	C3. Project parties relationship	2.73	3.50
	C4. Competence of team	2.96	3.80
	C5. Sharing values and culture in team	2.69	3.43
	C6. Encouraging creativity and innovation	2.85	3.33
	C7. Team involvement and building	2.88	3.43
	Sum Category C	**19.45**	**25.50**
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	2.50	3.56
	D2. Value Engineering awareness and frequency of implementation	2.75	3.61
	D3. Risk Management awareness and frequency of implementation	2.74	3.78
	D4. Accuracy of schedule accomplishment indicators (SPI)	2.84	3.47

	D5. Client focus	3.04	4.20
	D6. Problem solving and decision making	3.01	2.90
	D7. Flexibility of design	2.88	3.47
	Sum Category D	**19.75**	**24.98**
E. Technological Category	E1. Use of BIM	2.54	3.67
	E2. Effectiveness of using a scheduling tool	2.75	4.50
	Sum Category E	**5.28**	**8.17**
F. Contractual Category	F1. Procurement Plan	2.98	4.06
	F2. Appropriateness of project delivery method	2.88	4.03
	F3. Risk balance in contractual obligations	2.84	2.97
	Sum Category F	**8.70**	**11.06**

Consequently, in order to perform such comparison, two methods of analysis were done. First, the data were normalized in order to compare how experts from both countries rated the importance of each factor within its category. This was done by dividing the factor average by the sum of factor averages within the factor's category as seen in Table 10. The results showed that experts in USA and Egypt agreed on the order of importance of factors for three out of six of the categories. These categories being communication, technological and contractual categories. The identical opinions presented, gave an indication that there was a general agreement between the experts in both countries. This was also apparent in the behavioral category, despite the fact that the factor rankings were not identical, the variance in rank was not high to highlight a noteworthy difference in opinions. It can be concluded that the experts agreed on the ranking of 63% of the factors as only 10 factors out of the 27 had a difference in ranking that was higher than 1.

Table 10: Factor weighted average and factor rank within category comparison

	Factors:	Factor weighted average (USA)	Factor weighted average (EG)	Factor rank within category (USA)	Factor rank within category (EG)	Variance in rank
A. Behavioral Category	A1. Adaptation or resistance to change	24.28	23.26	3	4	1
	A2. Leadership and commitment	25.56	26.39	2	1	1
	A3. Continuous improvement	24.04	24.31	4	3	1
	A4. Trust, confidence and respect	26.13	26.04	1	2	1
	Sum Category A	**100**	**100**	-	-	-
B. Communication Category	B1. Frequency of meetings	22.58	22.01	4	4	-
	B2. Sharing of lessons learned	25.5	26.49	2	2	-
	B3. Early involvement of key stakeholders	27.25	26.87	1	1	-
	B4. Collective input in schedule development	24.67	24.63	3	3	-
	Sum Category B	**100**	**100**	-	-	-
C. Team category	C1. Team motivation and incentives	14.65	16.78	3	1	2
	C2. Orientation/workshops and training/education	12.81	14.6	7	3	4
	C3. Project parties relationship	14.02	13.73	5	4	1
	C4. Competence of team	15.23	14.9	1	2	1
	C5. Sharing values and culture in team	13.83	13.46	6	6	-
	C6. Encouraging creativity and innovation	14.65	13.07	4	7	3
	C7. Team involvement and building	14.81	13.46	2	5	3
	Sum Category C	**100**	**100**	-	-	-
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	12.66	14.23	7	4	3
	D2. Value Engineering awareness and frequency of implementation	13.94	14.46	5	3	2
	D3. Risk Management awareness and frequency of implementation	13.85	15.12	6	2	4
	D4. Accuracy of schedule accomplishment indicators (SPI)	14.37	13.88	4	6	2
	D5. Client focus	15.38	16.81	1	1	-
	D6. Problem solving and decision making	15.23	11.61	2	7	5
	D7. Flexibility of design	14.57	13.88	3	5	2
	Sum Category D	**100**	**100**	-	-	-
E. Technological Category	E1. Use of BIM	48.04	44.9	2	2	-
	E2. Effectiveness of using a scheduling tool	51.96	55.1	1	1	-
	Sum Category E	**100**	**100**	-	-	-
F. Contractual Category	F1. Procurement Plan	34.27	36.68	1	1	-
	F2. Appropriateness of project	33.08	36.48	2	2	-

	delivery method					
	F3. Risk balance in contractual obligations	32.65	26.83	3	3	-
	Sum Category F	**100**	**100**	**-**	**-**	**-**

The second step for analysis was done on the category level to know the order of importance of each category with respect to other categories. The same normalization logic was followed, the sum of factor averages for all factors within a category was divided by the sum of all the factor averages from Table 9. This gave the percentage contribution of each category as compared to all six categories. Additionally, it indicated the order of importance of each category. As seen in Figure 11, the six categories were ranked identically by the experts from both countries with the exception of the first category. The American experts ranked the most important category to be the managerial category while the Egyptian experts ranked it to be team category. However, since the variance in the percentage distribution is 1%, the difference in ranking can be associated to the different sample sizes. To conclude this comparison, it can be settled that there was no major difference between experts' opinions. The results showed that there was a general agreement on which factors were more important than others. Additionally, the variances in factors that were not identical were small which can be explained by either difference in personal opinions or again linked to the variation in sample size. Henceforth proving that the identified factors are not only applicable to all construction projects but also their level of influence on the projects will not vary despite the project's location. Subsequently, the factor averages obtained in Table 9 will hereinafter be used as the base reference that dictates the relative importance of factors when developing the scoring system.

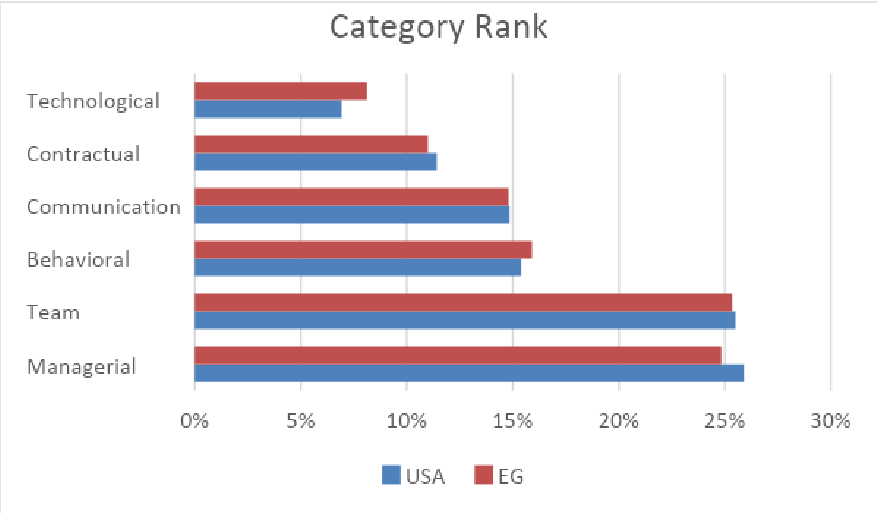


Figure 11: Ranked categories comparison based on percentage distribution

4.3 Developing Project Leanness Score

The analysis carried out previously gave reassurance that the factors chosen for the survey correctly give insight into a construction project. Moreover, it indicated that these factors, when implemented correctly, will enhance the project's overall efficiency. Since both surveys gave almost the same answers, the factor average of the USA survey was used in calculating the project leanness score. This is due to the fact that the USA survey sample size was larger, Americans were more familiar with lean principles and the average years of experience was higher than that of Egypt. The factor averages would then serve as the benchmark for calculating the performance score. The project leanness score developed follows a 100-point scale similar to the quality rating model developed by Hofacker (2008). The score was built to reflect the 5-point performance Likert scale presented in Table 11; where the performance of the company is measured according to its overall implementation of the identified lean factors. The total project score out of 100 would then indicate the overall frequency and quality of implementing lean factors in the project as outlined on the project leanness score scale seen in Figure 12. The score was calculated by multiplying the factor averages by 1 to get the minimum score and by 5 to get the maximum score as outlined in

Table 12. Then, the minimum and maximum scores were normalized by getting the score slope in order to fit the 100-point scale using

Equation 2. That way, theoretically speaking, if a company very frequently implements all 27 lean factors, it would score 5 on the Likert scale making its total score 100 as seen in Equation 3.

Table 11: Lean factors frequency and quality Likert scale representation

Factors:	**1**	**2**	**3**	**4**	**5**
Adaptation or resistance to change	0 to 20% of decision makers are flexible to adapt to change	20 to 40% of decision makers are flexible to adapt to change	40 to 60% of decision makers are flexible to adapt to change	60 to 80% of decision makers are flexible to adapt to change	80 to 100% of decision makers are flexible to adapt to change
Leadership and commitment	Extremely low sense of leadership and commitment	Somewhat low sense of leadership and commitment	Average sense of leadership and commitment	Somewhat high sense of leadership and commitment	Extremely high sense of leadership and commitment
Continuous improvement	0 to 20% of project employees show efforts in continuous improvement	20 to 40% of project employees show efforts in continuous improvemen t	40 to 60% of project employees show efforts in continuous improvement	60 to 80% of project employees show efforts in continuous improvemen t	80 to 100% of project employees show efforts in continuous improvemen t
Trust confidence and respect	Extremely low sense of trust and respect	Somewhat low sense of trust and respect	Average sense of trust and respect	Somewhat high sense of trust and respect	Extremely high sense of trust and respect
Frequency of meetings	Once every month	Biweekly	Weekly	More than once a week	Everyday
Sharing of lessons learned	No sharing	Rarely	Occasionally	Frequently	Very frequently
Early involvement of key stakeholders	Extremely low involvement	Somewhat low involvement	Average involvement	Somewhat high involvement	Extremely high involvement
Collective input in schedule development	Extremely low input	Somewhat low input	Average input	Somewhat high input	Extremely high input
Team motivation and incentives	Very rarely	Rarely	Occasionally	Frequently	Very Frequently
Orientation/workshops and training/education	Never	Once every year	Twice a year	Once every quarter	Once every two months
Project parties relationship	Very low	Low	Medium	High	Very high
Competence of team	Very low	Low	Medium	High	Very high
sharing values and culture in team	Very low	Low	Medium	High	Very high
Encouraging creativity and innovation	Very low	Low	Medium	High	Very high
Team involvement and building	Extremely low	Somewhat low	Average	Somewhat high	Extremely high

Lean construction awareness and frequency of implementation	Not aware of lean construction	Slightly aware with no adoption of lean Principles	Slightly aware with low implementation	Highly aware with some attempts to implement lean Principles	Highly aware of lean construction with regular implementation
Value Engineering awareness and frequency of implementation	Not aware of value engineering	Aware but never used in the project	Some attempts in value engineering were made but not applied	Applied once	Applied several times
Risk Management awareness and frequency of implementation	There is no risk management strategy	There is a risk management plan but it is not used	There is a risk management plan but it is not efficient	There is a risk management plan and it is sometimes used	There is a risk management plan and it is frequently used
Accuracy of schedule accomplishment indicators (SPI)	Extremely inaccurate	Somewhat inaccurate	Neutral	Somewhat accurate	Extremely accurate
Client focus	Extremely low	Somewhat low	Average	Somewhat high	Extremely high
Problem solving and decision making	0 to 20% of project employees demonstrate problem solving and decision-making skills	20 to 40% of project employees demonstrate problem solving and decision-making skills	40 to 60% of project employees demonstrate problem solving and decision-making skills	60 to 80% of project employees demonstrate problem solving and decision-making skills	80 to 100% of project employees demonstrate problem solving and decision-making skills
Flexibility of design	Extremely inflexible	Somewhat inflexible	Neutral	Somewhat flexible	Extremely flexible and well-coordinated
BIM	Not aware of BIM technology	Aware but BIM technology is not used	BIM technology is used only to fulfill a contract requirement	BIM technology is used in only one trade (structure, architecture or MEP)	BIM technology is used in multiple trades (structure, architecture and MEP)
Effectiveness of using a scheduling tool	Extremely ineffective	Somewhat ineffective	Neutral	Somewhat effective	Extremely effective
Procurement Plan	There is no procurement plan	There is a procurement plan but it is not used	There is a procurement plan but it is not efficient	There is a procurement plan and it is used sometimes	There is a procurement plan and it is used frequently
Appropriateness of project delivery	Extremely	Somewhat	Neutral	Somewhat	Extremely

method	inappropriate	inappropriat e		appropriate	appropriate
Risk balance in contractual obligations	Extremely imbalanced	Somewhat imbalanced	Neutral	Somewhat balanced	Extremely balanced

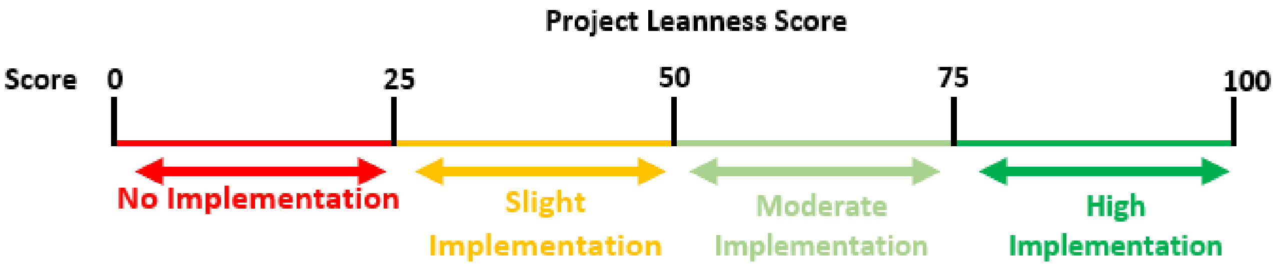


Figure 12: Project leanness score showing overall frequency of implementing lean factors

Table 12: Minimum and maximum scores

	Factors:	Factor average (x_i)	Minimum Score = x_i*1	Maximum Score = x_i*5
A. Behavioral Category	A1. Adaptation or resistance to change	2.85	2.85	14.25
	A2. Leadership and commitment	3.00	3.00	15
	A3. Continuous improvement	2.82	2.82	14.1
	A4. Trust, confidence and respect	3.07	3.07	15.35
	Sum Category A	**11.74**	**11.74**	**58.7**
B. Communication Category	B1. Frequency of meetings	2.56	2.56	12.8
	B2. Sharing of lessons learned	2.89	2.89	14.45
	B3. Early involvement of key stakeholders	3.08	3.08	15.4
	B4. Collective input in schedule development	2.79	2.79	13.95
	Sum Category B	**11.32**	**11.32**	**56.6**
C. Team category	C1. Team motivation and incentives	2.85	2.85	14.25
	C2. Orientation/workshops and training/education	2.49	2.49	12.45
	C3. Project parties relationship	2.73	2.73	13.65
	C4. Competence of team	2.96	2.96	14.8
	C5. Sharing values and culture in team	2.69	2.69	13.45
	C6. Encouraging creativity and innovation	2.85	2.85	14.25
	C7. Team involvement and building	2.88	2.88	14.4
	Sum Category C	**19.45**	**19.45**	**97.25**
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	2.50	2.50	12.5
	D2. Value Engineering awareness and frequency of implementation	2.75	2.75	13.75
	D3. Risk Management awareness and frequency of implementation	2.74	2.74	13.7
	D4. Accuracy of schedule accomplishment indicators (SPI)	2.84	2.84	14.2
	D5. Client focus	3.04	3.04	15.2
	D6. Problem solving and decision making	3.01	3.01	15.05
	D7. Flexibility of design	2.88	2.88	14.4
	Sum Category D	**19.75**	**19.75**	**98.75**
E. Technological Category	E1. Use of BIM	2.54	2.54	12.7
	E2. Effectiveness of using a scheduling tool	2.75	2.75	13.75
	Sum Category E	**5.28**	**5.28**	**26.4**
F. Contractual Category	F1. Procurement Plan	2.98	2.98	14.9
	F2. Appropriateness of project delivery method	2.88	2.88	14.4
	F3. Risk balance in contractual obligations	2.84	2.84	14.2
	Sum Category F	**8.70**	**8.70**	**43.5**
Sum of all categories		**76.25**	**76.25**	**381.2**

Equation 2: Total leanness score slope equation

$$Leanness\ score\ slope = \frac{100}{\sum_{i=category\ A}^{Category\ F} x_i * \max of\ Likert\ Scale - \sum_{i=Category\ A}^{Category\ F} x_i * \min of\ Likert\ Scale} =$$

$$\frac{100}{381.2-76.25} = 0.33$$

Equation 3: Total leanness score calculation method

$$Leanness\ score = \left(\sum_{j=Category\ A}^{Category\ F} P_j * \sum_{i=Category\ F}^{Category\ F} x_i - \sum_{i=Category\ A}^{Category\ F} x_i * \min of\ likert\ scale\right) * leanness\ score\ slope$$

- Where P_j is the company's self-rated lean factor implementation frequency based on the Likert scale.

The total score gives an indication on how frequently the company is applying lean factors holistically. However, in order to facilitate the process of arranging an action plan to improve performance, a more detailed analysis was done. This analysis dissects the company's score with respect to the six lean categories. To do that, a category score slope and a category total score were calculated for each of the six categories as seen in Equation 4 through Equation 15. That way, the scoring model would be able to highlight areas of weakness and strength for companies based on their highest and lowest scoring categories. Thus, enabling companies to lay out a strategic plan for how they want to move forward in their projects.

Equation 4: Behavioral category slope equation

$$Behavioral\ Category\ score\ slope = \frac{100}{{}_{i=Factor\ A1}^{Factor\ A4}\Sigma x_i * max\ of\ Likert\ Scale - {}_{i=Factor\ A1}^{Factor\ A4}\Sigma x_i * min\ of\ Likert\ Scale}$$

$$= \frac{100}{58.7 - 11.74} = 2.13$$

Equation 5: Behavioral category score calculation method

$$Behavioral\ category\ total\ score = \left(\sum_{j=Factor\ A1}^{Factor\ A4} P_j * \sum_{i=Factor\ A1}^{Factor\ A4} x_i - \sum_{i=Factor\ A1}^{Factor\ A4} x_i * \min of\ likert\ scale\right) * Behavioral\ category\ score\ slope$$

Equation 6: Communication category slope equation

$$Communication\ Category\ score\ slope = \frac{100}{{}_{i=Factor\ B1}^{Factor\ B4}\Sigma x_i * max\ of\ Likert\ Scale - {}_{Factor\ B1}^{Factor\ B4}\Sigma x_i * min\ of\ Likert\ Scale}$$

$$= \frac{100}{56.6 - 11.32} = 2.2$$

Equation 7: Communication category score calculation method

$$Communication\ category\ total\ score = \left(\sum_{j=Factor\ B1}^{Factor\ B4} P_j * \sum_{i=Factor\ B1}^{Factor\ B4} x_i - \sum_{i=Factor\ B1}^{Factor\ B4} x_i * \min of\ likert\ scale\right) * Communication\ category\ score\ slope$$

Equation 8: Team category slope equation

$$Team\ Category\ score\ slope = \frac{100}{{}_{i=Factor\ C1}^{Factor\ C7}\Sigma x_i * max\ of\ Likert\ Scale - {}_{i=Factor\ C1}^{Factor\ C7}\Sigma x_i * min\ of\ Likert\ Scale} = \frac{100}{97.25 - 19.45} = 1.3$$

Equation 9: Team category score calculation method

$$Team\ category\ total\ score = \left(\sum_{j=Factor\ C1}^{Factor\ C7} P_j * \sum_{i=Factor\ C1}^{Factor\ C7} x_i - \sum_{i=Factor\ C1}^{Factor\ C7} x_i * \min of\ likert\ scale\right) * Team\ category\ score\ slope$$

Equation 10: Managerial category slope equation

$$Managerial\ Category\ score\ slope = \frac{100}{{}_{i=Factor\ D1}^{Factor\ D7}\Sigma x_i * max\ of\ Likert\ Scale - {}_{i=Factor\ D1}^{Factor\ D7}\Sigma x_i * min\ of\ Likert\ Scale} = \frac{100}{98.75 - 19.75} = 1.26$$

Equation 11: Managerial category score calculation method

$$Managerial\ category\ total\ score = \left(\sum_{j=Factor\ D1}^{Factor\ D7} P_j * \sum_{i=Factor\ D1}^{Factor\ D7} x_i - \sum_{i=Factor\ D1}^{Factor\ D7} x_i * \min of\ likert\ scale\right) * Managerial\ category\ score\ slope$$

Equation 12: Technological category slope equation

$$Technological\ Category\ score\ slope = \frac{100}{{}_{i=Factor\ E1}^{Factor\ E2}\Sigma x_i * max\ of\ Likert\ Scale - {}_{i=Factor\ E1}^{Factor\ E2}\Sigma x_i * min\ of\ Likert\ Scale} = \frac{100}{26.4 - 5.28} = 4.73$$

Equation 13: Technological category score calculation method

$$\begin{aligned}&Technological\ category\ total\ score\\&= \left(\sum_{j=Factor\ E1}^{Factor\ E2} P_j * \sum_{i=Factor\ E1}^{Factor\ E2} x_i - \sum_{i=Factor\ \ E1}^{Factor\ E2} x_i * \min of\ likert\ scale\right)\\&* Technological\ category\ score\ slope\end{aligned}$$

Equation 14: Contractual category slope equation

$$\begin{aligned}&Contractual\ Category\ score\ slope\\&= \frac{100}{{}_{i=Factor\ F1}^{Factor\ F3}\Sigma x_i * max\ of\ Likert\ Scale\ -\ {}_{i=Factor\ F1}^{Factor\ F3}\Sigma x_i * min\ of\ Likert\ Scale}\\&= \frac{100}{43.5-8.7} = 2.87\end{aligned}$$

Equation 15:Contractual category score calculation method

$$\begin{aligned}&Contractual\ category\ total\ score\\&= \left(\sum_{j=Factor\ F1}^{Factor\ F3} P_j * \sum_{i=Factor\ F1}^{Factor\ F3} x_i - \sum_{i=Factor\ \ E1}^{Factor\ F3} x_i * \min of\ likert\ scale\right)\\&* Contractual\ category\ score\ slope\end{aligned}$$

4.3.1. *Example on Calculating Project Leanness Score for a Hypothetical Project*

To further illustrate how a company's performance score is calculated using the project leanness score equation, take the hypothetical case of XYZ Company as an example. First, XYZ Company will participate in a self-rating survey where it will rate its project performance in the 27 lean factors. The rating of the factors is done based on the aforementioned lean factors Likert scale. The self-rating scores of XYZ Company would be as shown in Table 13.

Table 13: XYZ Company self-ratings

	Factors:	Factor Averages (x_i)	XYZ Company (P_j)	Factor score ($x_i * P_j$)
A. Behavioral Category	A1. Adaptation or resistance to change	2.85	2	5.7
	A2. Leadership and commitment	3	4	12.0
	A3. Continuous improvement	2.82	5	14.1
	A4. Trust, confidence and respect	3.07	4	12.3
	Sum Category A	**11.74**	**15**	**44.1**
B. Communication Category	B1. Frequency of meetings	2.56	3	7.7
	B2. Sharing of lessons learned	2.89	3	8.7
	B3. Early involvement of key stakeholders	3.08	4	12.3
	B4. Collective input in schedule development	2.79	4	11.2
	Sum Category B	**11.32**	**14**	**39.8**
C. Team category	C1. Team motivation and incentives	2.85	3	8.6
	C2. Orientation/workshops and training/education	2.49	4	10.0
	C3. Project parties relationship	2.73	3	8.2
	C4. Competence of team	2.96	3	8.9
	C5. Sharing values and culture in team	2.69	3	8.1
	C6. Encouraging creativity and innovation	2.85	4	11.4
	C7. Team involvement and building	2.88	4	11.5
	Sum Category C	**19.45**	**24**	**66.6**
D. Managerial Category	D1. Lean construction awareness and frequency of implementation	2.5	4	10.0
	D2. Value Engineering awareness and frequency of implementation	2.75	5	13.8
	D3. Risk Management awareness and frequency of implementation	2.74	4	11.0
	D4. Accuracy of schedule accomplishment indicators (SPI)	2.84	4	11.4
	D5. Client focus	3.04	4	12.2
	D6. Problem solving and decision making	3.01	2	6.0
	D7. Flexibility of design	2.88	3	8.6
	Sum Category D	**19.76**	**26**	**72.9**
E.	E1. Use of BIM	2.54	4	10.2

Technological Category	E2. Effectiveness of using a scheduling tool	2.75	5	13.8
	Sum Category E	**5.29**	**9**	**23.9**
F. Contractual Category	F1. Procurement Plan	2.98	4	11.9
	F2. Appropriateness of project delivery method	2.88	3	8.6
	F3. Risk balance in contractual obligations	2.84	3	8.5
	Sum Category F	**8.7**	**10**	**29.1**
Sum of all categories		**76.25**	**76**	**276.4**

To calculate the total score for XYZ Company, Equation 3 would be utilized as follows

$$Leanness\ score = \left(\sum_{j=Category\ A}^{Category\ F} P_j * \sum_{i=Category\ A}^{Category\ F} x_i - \sum_{i=Category\ A}^{Category\ F} x_i * min\ of\ likert\ scale\right) * \ leanness\ score\ slope = (276.4 - 76.25) * 0.33 = 66$$

Hence, the total score for XYZ Company will be 66 points out of 100. This means that XYZ Company moderately implements the lean factors based on the project leanness score established. To further dissect XYZ's performance in the project, one can calculate the category scores for each of the six categories using the established equations. Doing that allows for a closer inspection of the company's performance in the project through assessing the lowest performing categories and setting a way forward plan for performance to pick up. Below are the calculated category scores out of 100 for XYZ Company.

$$Behavioral\ Category\ score = \left(\sum_{j=Factor\ A1}^{Factor\ A4} P_j * \sum_{i=Factor\ A1}^{Factor\ A4} x_i - \sum_{i=Factor\ A1}^{Factor\ A4} x_i * \min of\ likert\ scale\right) * Behavioral\ category\ score\ slope = (44.1 - 11.74) * 2.13 = 69$$

$$Communication\ Category\ score = \left(\sum_{j=Factor\ B1}^{Factor\ B4} P_j * \sum_{i=Factor\ B1}^{Factor\ B4} x_i - \sum_{i=Factor\ B1}^{Factor\ B4} x_i * min\ of\ likert\ scale\right) * Communication\ category\ score\ slope = (39.8 - 11.32) * 2.2 = 62$$

$$Team\ Category\ score = \left(\sum_{j=Factor\ C1}^{Factor\ C7} P_j * \sum_{i=Factor\ C1}^{Factor\ C7} x_i - \sum_{i=Factor\ C1}^{Factor\ C7} x_i * min\ of\ likert\ scale\right) * Team\ category\ score\ slope = (66.6 - 19.45) * 1.3 = 61$$

$$Managerial\ Category\ score =$$

$$= (\sum_{j=Factor\ D1}^{Factor\ D7} P_j * \sum_{i=Factor\ D1}^{Factor\ D7} x_i - \sum_{i=Factor\ \ D1}^{Factor\ D7} x_i * min\ of\ \ likert\ scale)$$

$$* Managerial\ category\ score\ slope = (72.9 - 19.76) * 1.26 = 67$$

$$Technological\ Category\ score =$$

$$= (\sum_{j=Factor\ E1}^{Factor\ E2} P_j * \sum_{i=Factor\ E1}^{Factor\ E2} x_i - \sum_{i=Factor\ \ E1}^{Factor\ E2} x_i * min\ of\ \ likert\ scale)$$

$$* Technological\ category\ score\ slope = (23.9 - 5.29) * 4.73 = 88$$

$$Contractual\ Category\ score =$$

$$= (\sum_{j=Factor\ F1}^{Factor\ F3} P_j * \sum_{i=Factor\ F1}^{Factor\ F3} x_i - \sum_{i=Factor\ \ F1}^{Factor\ F3} x_i * min\ of\ \ likert\ scale)$$

$$* Contractual\ category\ score\ slope = (29.1 - 8.7) * 2.87 = 59$$

The calculated category scores show that XYZ Company’s weakest performing area is the contractual category and its strongest performing area is the technological category. Consequently, XYZ Company can use the category scores in setting action plans to further improve the company’s implementation of lean principles. A more detailed evaluation of XYZ Company can be done through comparing its performance scores to other companies’ performance scores. That way, XYZ Company can not only asses it’s performance against itself, but also against other companies in the industry. In order to do that, a project-based survey was created.

4.4 Data Collection – Project-Based Survey

After developing the scoring system, a project-based survey was created in order to gather information on industry performance in construction projects. The survey aimed to make the respondent self-rate their companies' performance in a specific project. To be able to gather the widest variety of projects, no selection criteria were applied. This means that the survey could take responses from people who work for contractors, consultants or employers on projects that were either completed or ongoing, in or out of Egypt and all project types (residential, offices, bridges etc.). The survey was divided into two sections: project information and lean factors. The project information section focused on the general data about the project. It collected information such as the company's role in the project, its current status (completed or ongoing), its type, the planned and expected/actual duration, and finally the planned and expected/actual budget. After entering the project's information, the respondents were directed to the second section of the survey which is the lean factors section. In this section, they were asked to rate the company's performance in each of the 27 lean factors. The rating was also done on a 5-point Likert scale with 1 being the lowest rating and 5 being the highest. The survey questions can be referred to in Table 11.

A total of 30 responses were collected through the survey; each response representing and describing a different project. Projects collected were of 10 distinct types with the majority of them being residential - the distribution of project types is displayed in Figure 13. The variety of projects guarantees that the scoring system is inclusive of several kinds of projects. This inclusivity broadens the database upon which the scores are calculated; thus, improving the chances of correctly predicting scores for future users. Moreover, the projects had different statuses, 30% of which were completed and 70% were still ongoing, similarly making the database comprehensive of both cases. The survey responses also included projects where the company was either working as the consultant, contractor or employer as per Figure 14, representing all major roles in a construction project. Aside from the all-inclusive case representation, the preliminary analysis of the data showed that all different project statuses were depicted. This means that the data contained projects that belonged to one of four categories: early/on time and on/under budget, early/on time and above budget, delayed and on/under budget or delayed and above budget. The Venn diagrams in Figure 15 show the data distribution demonstrating the projects' status in terms of their standpoint on schedule and budget progress. The aforementioned further emphasizes the extensive range of the database documented through the responses collected. Thus, pushing forward to the successive part of the research, which is finding a correlation between lean factors and project performance through data analysis.

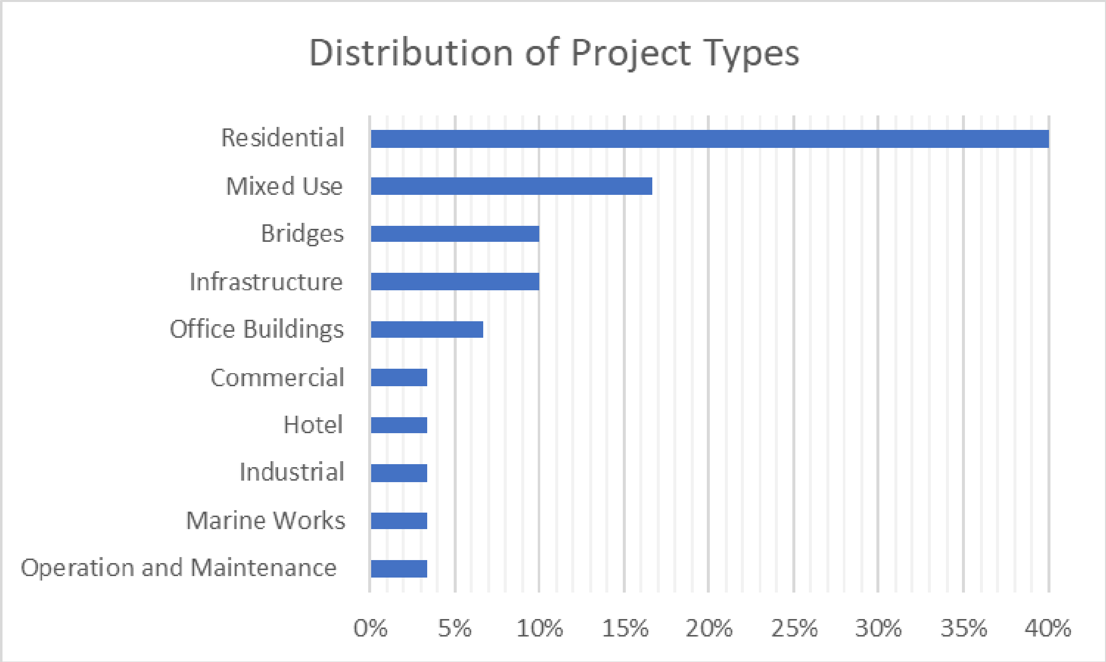


Figure 13: Distribution of project types

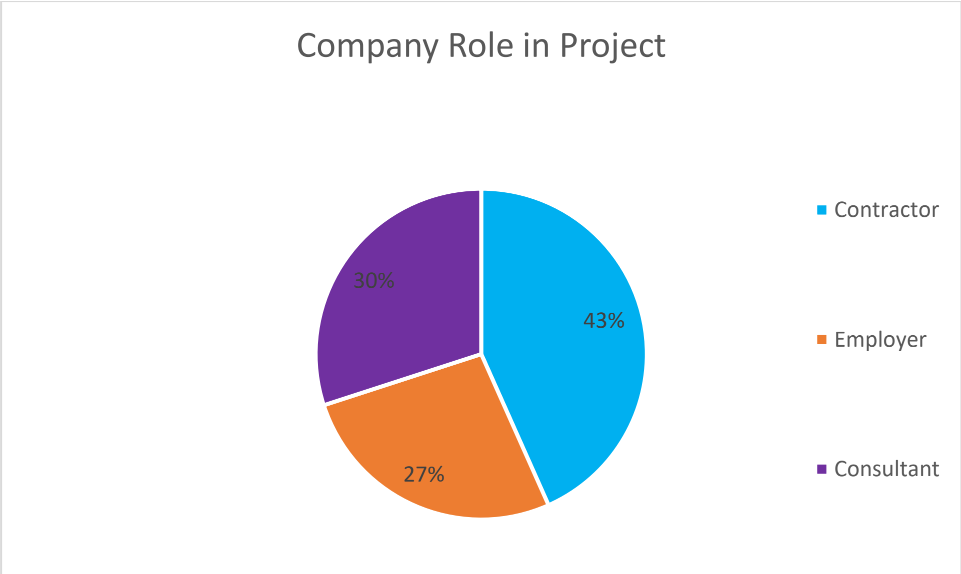


Figure 14: Company role in project

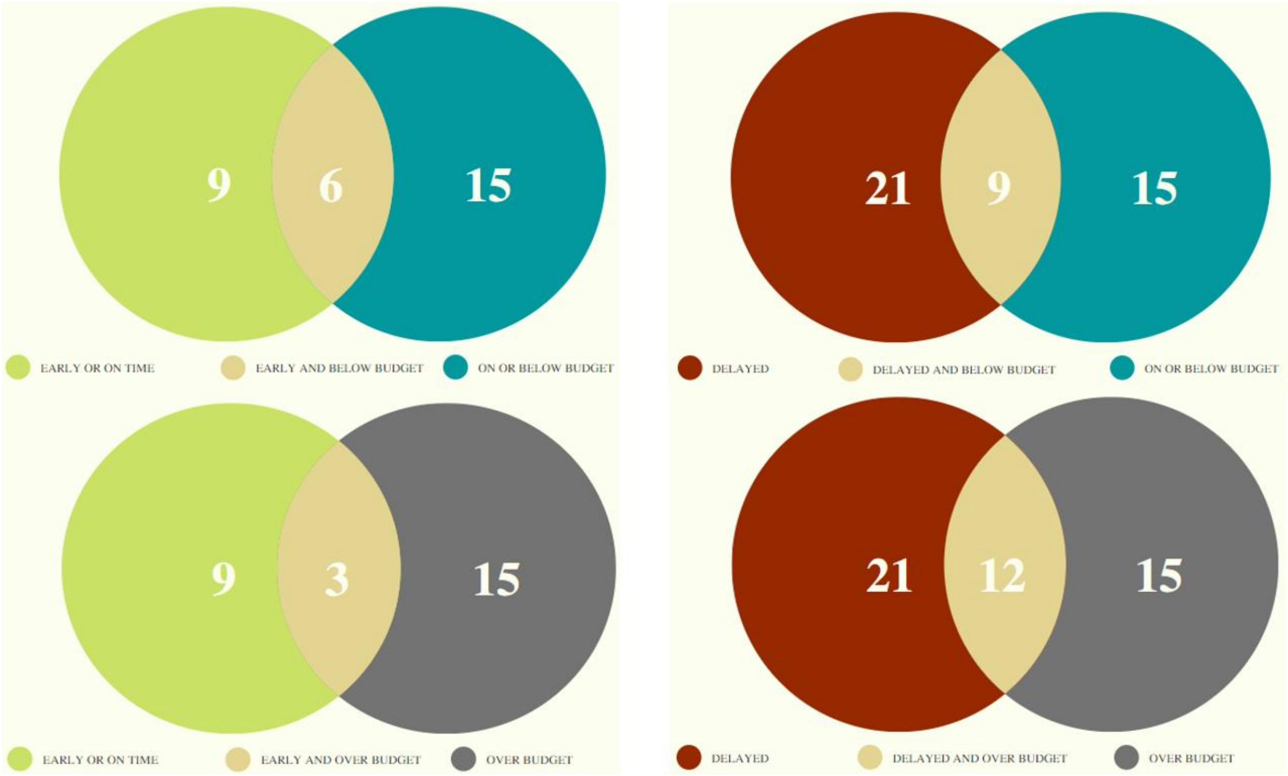


Figure 15: Venn diagrams demonstrating the projects' status

4.5 Benchmarking the Performance Score

To perform data analysis, the first step was to calculate the category scores and total score for each project as per the scoring system established in section 4.3 of the research. The resulting category scores and total score of the 30 projects in the database are shown in Figure 16 below. From the box plots, one can observe that the industry's performance level varied from one category to the other. The higher the variability in performance level, the larger the height of the box plot. In that case, the category with the most variability in performance was the technological category. Conversely, the category with least variability was the managerial category. Additionally, it should be noted that the communication category was the weakest performing category among all 30 projects. As seen, the project scoring the highest in the communication category scored 69.5 out of 100. This indicates a general area of weakness in communication among all project teams for the 30 projects in the database. On the other hand, the technology category had a wide range of performance levels, however the majority of projects scored high on this category indicating a general area of strength.

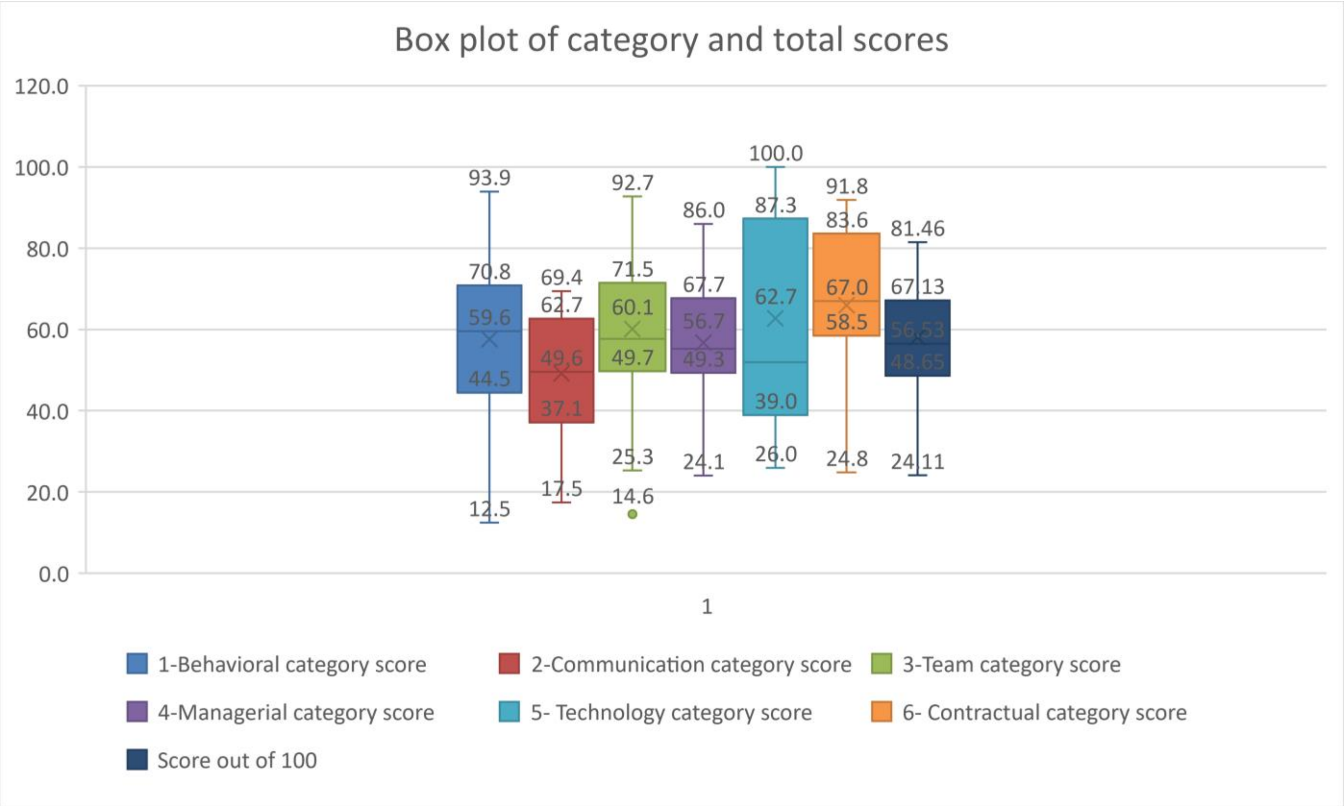


Figure 16: Box plot showing projects' category and total scores

To be able to properly asses future users' input data, the database for category scores and total scores were divided into six quartiles using the quartiles established in the box plots as seen in figure Figure 17 through Figure 23 below. The established leanness benchmarking scale helps in providing a more accurate and fair performance assessment as it uses the industry performance as the datum of the assessment. Hence, giving the user a complete assessment that consists of two main insights. The first is the total score which represents the company's overall quality and frequency of implementing lean factors in the project. The second is benchmarking the project's category and total scores as compared to other companies in the field. The benchmarking scales give the user a deeper understanding of what the achieved scores mean as compared to the overall industry performance. For example, if a user scored 57 out of 100 in the contractual category, they may be compelled to think that this score is average so they do not need to set an action plan to improve in this category. However, the contractual category benchmarking scale would show the user that a score of 57 is actually considered poor performance as compared to other companies in the industry. Therefore, spotting a light on weak performance areas that need improvements.

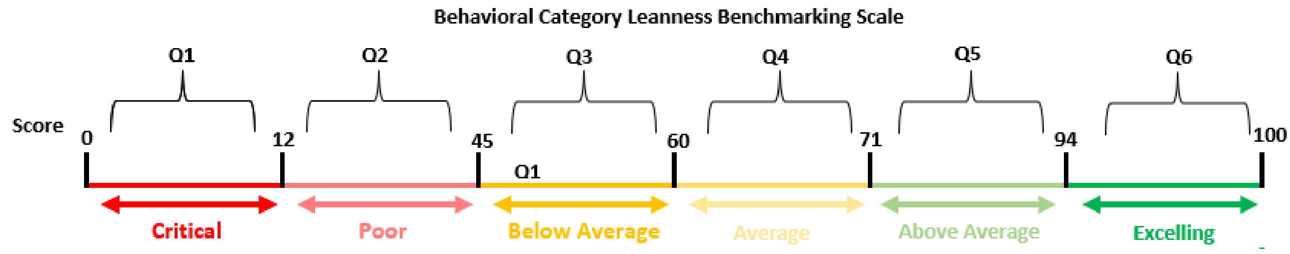


Figure 17: Behavioral Category leanness Benchmarking scale

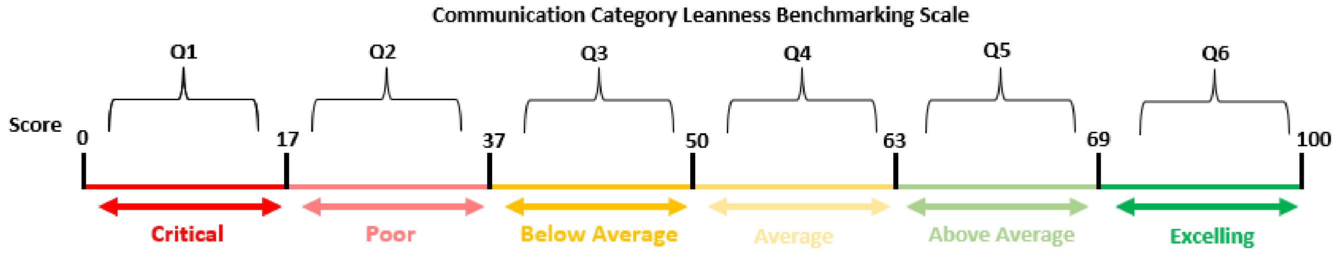


Figure 18: Communication Category leanness Benchmarking scale

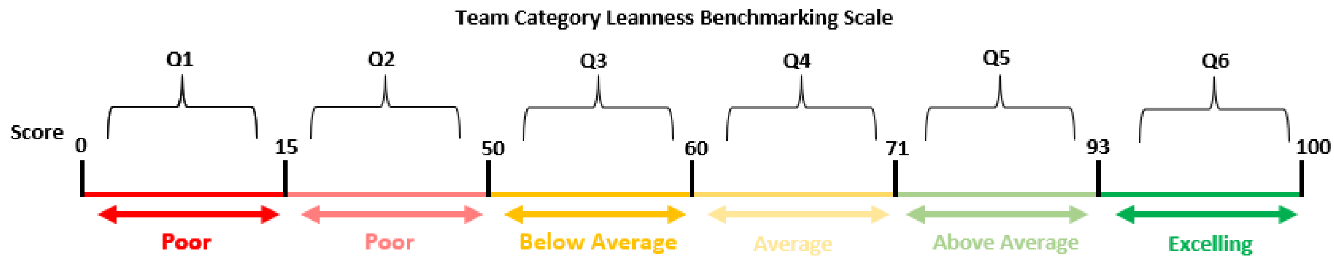


Figure 19: Team Category leanness Benchmarking Scale

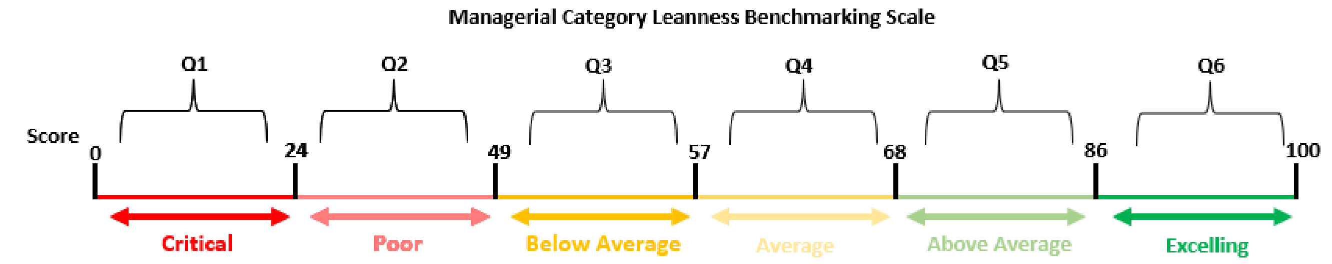


Figure 20: Managerial Category leanness Benchmarking Scale

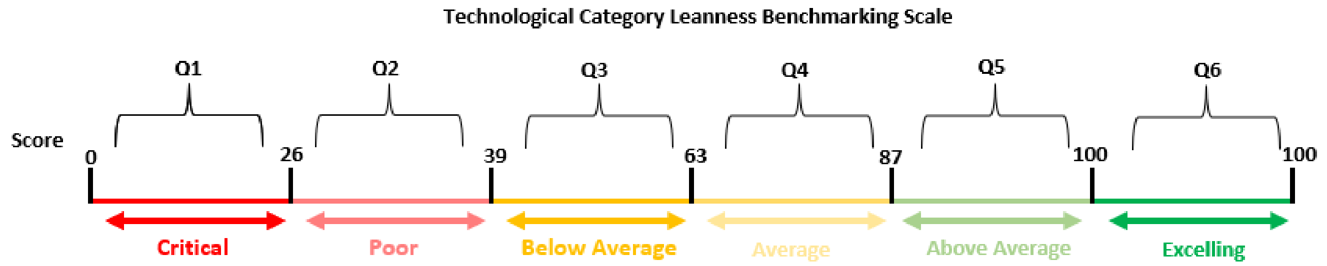


Figure 21: Technological Category leanness Benchmarking Scale

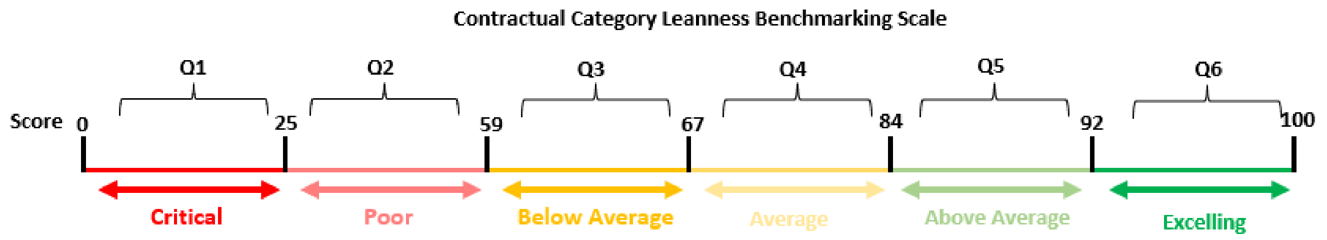


Figure 22: Contractual Category leanness Benchmarking Scale

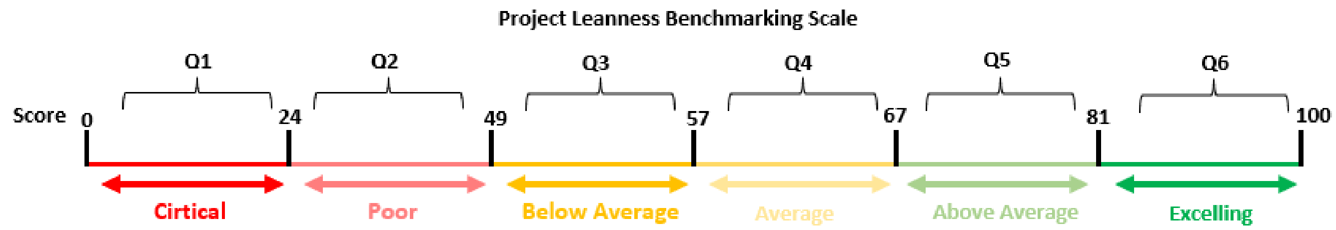


Figure 23: Project Leanness Benchmarking Scale

Chapter 5. Developing Performance Prediction Model

5.1 Descriptive Statistics

In an effort to establish a correlation between scores and project performance, the percentages of schedule and budget variance were calculated and the project status was derived from these percentages as seen from

Table 14. As an initial attempt in finding a correlation between lean factors and project performance, a visual inspection was done to check if there is a connection between scores and schedule variance. The trendline of the scatter plot in Figure 24 shows a general pattern that the higher the lean factor score is, the lower the schedule variance. This is also apparent from the data analysis presented in Table 15 as the average schedule variance decreased when the score range increased. Another important observation was that the variance range decreased by almost 30% as the score increased. Meaning that the better the company's implementation of lean factors, the more persistent its performance is and accordingly the less the deviation from the planned duration of the project. As for the correlation between total score and budget variance, there is no obvious pattern that could be identified solely through visual inspection as displayed in Figure 25. Hence, prompting a more profound look into the data through machine learning algorithms.

Table 14: Projects' score and status

Project	Total score out of 100	Schedule Variance (%)	Budget Variance (%)	Status
1	49	-13%	20%	Early/on time and above budget
2	58	25%	7%	Delayed and above budget
3	53	1%	-2%	Delayed and on/under budget
4	56	17%	-14%	Delayed and on/under budget
5	66	33%	0%	Delayed and on/under budget
6	69	10%	0%	Delayed and on/under budget
7	53	1%	-2%	Delayed and on/under budget
8	67	1%	3%	Delayed and above budget
9	24	100%	6%	Delayed and above budget
10	56	8%	35%	Delayed and above budget
11	45	25%	0%	Delayed and on/under budget
12	80	0%	-8%	Early/on time and on/under budget
13	48	16%	0%	Delayed and above budget
14	52	40%	21%	Delayed and above budget
15	62	17%	18%	Delayed and above budget
16	39	30%	1%	Delayed and above budget
17	42	29%	5%	Delayed and above budget

18	76	-3%	3%	Early/on time and above budget
19	47	0%	0%	Early/on time and on/under budget
20	50	-1%	-8%	Early/on time and on/under budget
21	75	5%	1%	Delayed and above budget
22	66	18%	-2%	Delayed and on/under budget
23	59	7%	9%	Delayed and above budget
24	48	-65%	1%	Early/on time and above budget
25	57	31%	-18%	Delayed and on/under budget
26	60	-20%	-7%	Early/on time and on/under budget
27	74	12%	10%	Delayed and above budget
28	52	10%	0%	Delayed and on/under budget
29	81	-4%	-5%	Early/on time and on/under budget
30	80	-10%	-3%	Early/on time and on/under budget

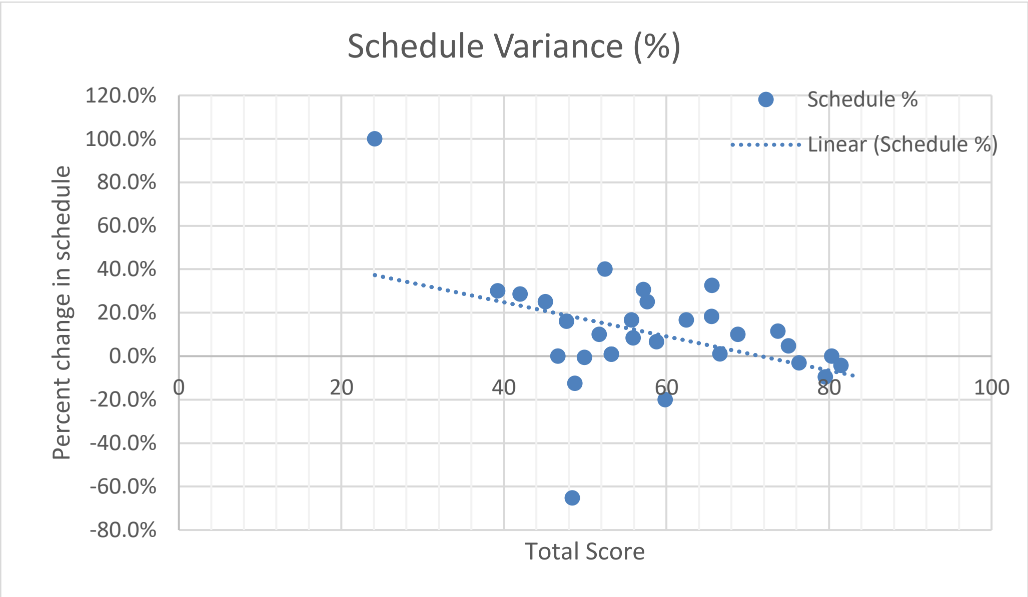


Figure 24: Relationship between total score and schedule variance

Table 15: Data analysis for schedule variance vs. total score

	Schedule Variance (%)			Variance Range (Max-Min)	No. of projects
Score	**Min**	**Max**	**Avg.**		
<40	Not enough data				1
40-60	-20	40	12.1	60	17
60-80	-9.6	32	7.1	41.6	11
>80	Not enough data				1

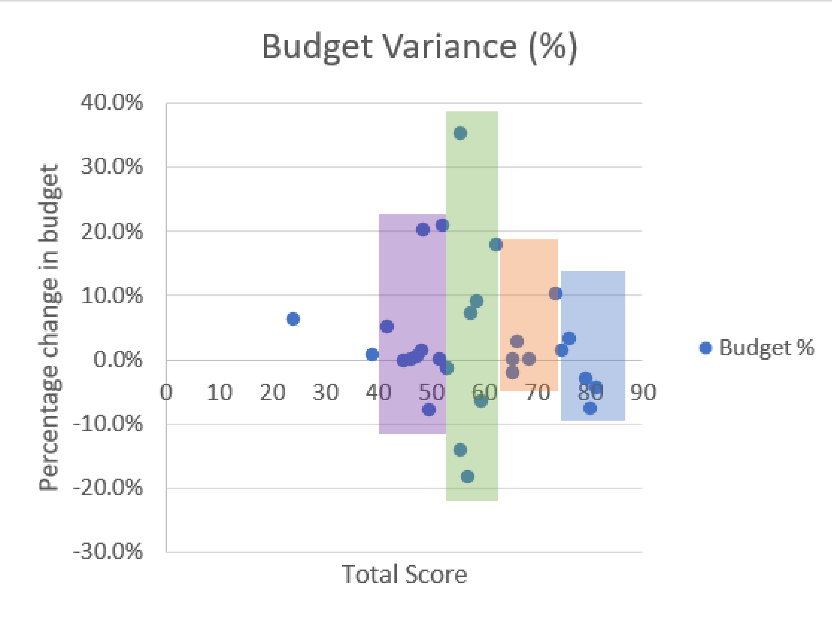


Figure 25: Relationship between total score and budget variance

5.2 Machine Learning Algorithms

5.2.1. Numerical Analysis

5.2.1.1. Linear Regression

To further understand the correlation between lean factors and project performance, a closer look into the projects was required. First, a breakdown of the total score was done by calculating the category scores to get a deeper understanding of the project's performance. Dissecting the total score was done for two main aims; a) to observe if a certain lean factor category was more influential in affecting project performance than others and b) to see if an equation can be developed to numerically estimate project duration and budget. The score breakdown, presented in Table 16, was used to calculate linear correlation. The results displayed in Table 17 show that the variables seem to have a rather weak linear relationship, especially with the schedule and budget variables.

Table 16: Project score breakdown

Project	Behavioral category score out of 100	Communication category score out of 100	Team category score out of 100	Managerial category score out of 100	Technological category score out of 100	Contractual category score out of 100	Total score out of 100
1	44	63	25	61	26	75	49
2	82	43	58	56	39	58	58
3	50	49	47	58	52	67	53
4	32	50	54	57	75	84	56
5	69	63	61	67	88	59	66
6	39	69	71	78	52	92	69
7	50	49	47	58	52	67	53
8	81	43	68	57	100	75	67
9	12	33	15	24	52	33	24
10	68	57	57	54	52	42	56
11	50	31	43	47	100	25	45
12	81	68	89	79	100	67	80
13	50	17	58	51	39	59	48
14	39	43	54	51	52	84	52
15	81	51	64	51	75	67	62
16	45	30	50	33	39	33	39
17	57	24	57	33	52	25	42
18	63	63	89	86	52	75	76
19	31	39	46	51	52	67	47
20	69	51	58	37	39	42	50
21	94	62	73	76	52	84	75
22	69	56	65	69	39	84	66
23	56	44	65	55	63	75	59
24	44	31	50	50	37	75	48
25	63	49	57	47	100	59	57
26	75	69	75	37	39	59	60
27	63	69	89	66	76	76	74
28	26	31	49	54	87	92	52
29	69	68	93	76	100	92	81
30	75	61	78	83	100	92	80

Table 17: Linear correlation between scores and project performance

Variable	Behavioral category	Communication category	Team category	Managerial category	Technological category	Contractual category	Total score out of 100	Schedule Variance	Budget Variance
Behavioral category	1.00	0.48	0.66	0.40	0.21	0.08	0.68	-0.31	-0.01
Communication category		1.00	0.59	0.66	0.18	0.47	0.77	-0.27	-0.03
Team category			1.00	0.65	0.37	0.43	0.89	-0.37	-0.19
Managerial category				1.00	0.32	0.72	0.87	-0.37	-0.06
Technological category					1.00	0.18	0.45	0.09	-0.31
Contractual category						1.00	0.65	-0.42	-0.10
Total score out of 100							1.00	-0.40	-0.15
Schedule Variance								1.00	0.10
Budget Variance									1.00

This was further corroborated when a multi variate linear regression was performed once between the scores (independent variables) and project duration (dependent variable) and a second time between the scores and project budget. The regression equation predicting project duration can be seen in Table 18. From the coefficients of the equation, one can observe that all the category scores (dependent variables) are negative, which means that they are inversely related to the project duration. Therefore, the regression equation is suggesting that the higher a project scores in each of the lean categories, the shorter the project duration will be. This general hypothesis of the equation is reasonable; however, one cannot rely solely on the coefficients when evaluating the accuracy of regression equation. Hence, the p-value for each of the coefficients were assessed. The p-value is a statistical term that tests the null hypothesis that the coefficient has no effect in the equation, if the p-value is lower than 5% then this means that the regression equation is reliable. Giving a closer look to the P-values of the regression equation, one can observe that none of them were lower than 5%. Moreover, as seen in Table 19 the equation had a very low adjusted R values of 0.13 and a high significance F value of 17% while its accepted values should be below 5%. The same analysis was carried out for the regression equation predicting the project budget and similar results were found. Table 20 shows that the equation establishes an inverse relationship between the category scores and the project budget through the negative coefficients. However, the P-values for all coefficients were higher than 5%. Additionally, Table 21 shows an adjusted R squared of -0.06 and a significance F of 63% which is not accepted. This gave a sign that linear data analysis is not the best method to analyze the data. Hence, compelling a redirection of the data analysis approach to follow different predictive data analytics tools.

Table 18: Linear regression equation predicting project duration

Regression equation predicting project duration	Coefficients	P-value
Intercept	0.462	0.062

Behavioral category scores out of 100	-2.568	0.383
Communication category score out of 100	-2.473	0.385
Team category score out of 100	-4.253	0.384
Managerial category scores out of 100	-4.3201	0.384
Technological category scores out of 100	-1.151	0.385
Contractual category scores out of 100	-1.906	0.383
Total score out of 100	16.668	0.384

Table 19: Regression statistics for project duration

Regression Statistics for project duration	
Multiple R	0.587
R Square	0.344
Adjusted R Square	0.136
Standard Error	0.242
Significance F	0.172
Observations	30

Table 20: Linear regression equation predicting project budget

Regression equation predicting project budget	*Coefficients*	*P-value*
Intercept	0.051	0.635
Behavioral category score out of 100	-1.516	0.258
Communication category score out of 100	-1.463	0.258
Team category score out of 100	-2.516	0.258
Managerial category score out of 100	-2.553	0.259
Technological category score out of 100	-0.684	0.257
Contractual category score out of 100	-1.125	0.258
Total score out of 100	9.858	0.258

Table 21: Regression statistics for project budget

Regression Statistics for project budget	
Multiple R	0.439
R Square	0.192
Adjusted R Square	-0.063
Standard Error	0.109
Significance F	0.632
Observations	30

5.2.1.2. Non-linear Regression

Since it is established that the relationship between scores and schedule and budget variance is non-linear. Another attempt in numerical analysis is done through non-linear regression. This analysis was aided through excel add-in XLSTAT (Addinsoft, 2020) where it performed non-linear regression analysis. The first trial run of non-linear regression aimed to see if an equation can be developed to predict the durations of projects based on their scores. When setting up the model, category scores were the independent variables and the percentage change in project duration was the dependent variable. The preliminary results of the non-linear regression model showed that the software, after 33 automatic iterations, chose the sin equation to be the best fitting equation describing the data. Where, from Equation 16, pr1 to pr4 are parameters or constant coefficients that the software calculated and X1 to X6 are the six lean category scores. The values of the parameters can be seen from Table 22, as an initial inspection, the equation's accuracy of prediction is not expected to be high as both the standard error and the confidence interval results did not show high precision. Moreover, the adjusted R^2 of the regression model is 0.01 which is very low and highlights great inaccuracy of the model.

Equation 16: Non-linear regression equation predicting percent change in project duration

$$\begin{aligned}\%\ change\ of\ project\ duration &= pr1 + pr2 * sin(pr3 * X1 + pr4) + pr2 * sin(pr3 * X2 + pr4) + pr2 \\ &* sin(pr3 * X3 + pr4) + pr2 * sin(pr3 * X4 + pr4) + pr2 * sin(pr3 * X5 \\ &+ pr4) + pr2 * sin(pr3 * X6 + pr4)\end{aligned}$$

Table 22: Parameters of non-linear equation predicting percent change in project duration

Parameters	Value	Standard error	Lower bound (95%)	Upper bound (95%)
pr1	0.107	0.053	-0.001	0.215
pr2	-0.049	0.032	-0.115	0.017
pr3	1.364	0.260	0.829	1.899
pr4	-1.939	2.432	-6.939	3.060

The equation's prediction results can be seen from Table 23, it is concluded from the high residuals that the model is not accurate especially that the highest residual reached up to 87%. Additionally, the mean absolute error of the model is approximately 250% which is not accepted due to its high inaccuracy. XLSTAT also generated a graphical representation of the residuals of prediction as seen in Figure 26 that further shows the inaccuracy of the model.

Table 23: Prediction results of non-linear regression for percent change in project duration

Planned duration (weeks)	Forecasted duration (weeks)	Percent change in project duration	Predicted change in project duration	Residual
96	84	-12.5%	20%	-33%
192	240	25.0%	14%	11%
138	139	0.9%	16%	-15%
72	84	16.7%	14%	3%
528	700	32.6%	18%	14%
20	22	10.0%	3%	7%
138	139	0.9%	16%	-15%
197	199	1.0%	8%	-7%
192	384	100.0%	13%	87%
12	13	8.3%	16%	-8%
32	40	25.0%	9%	16%
209	209	0.0%	4%	-4%
25	29	16.0%	25%	-9%
130	182	40.0%	3%	37%
48	56	16.7%	15%	2%
10	13	30.0%	-3%	33%
14	18	28.6%	20%	9%
128	124	-3.1%	6%	-10%
240	240	0.0%	-1%	1%
187	186	-0.5%	2%	-3%
105	110	4.8%	11%	-6%
984	1163	18.2%	10%	8%
90	96	6.7%	20%	-13%
576	200	-65.3%	0%	-66%
157	205	30.6%	22%	9%
15	12	-20.0%	-1%	-19%
104	116	11.5%	8%	4%
260	286	10.0%	11%	-1%
190	182	-4.2%	11%	-15%
209	189	-9.6%	7%	-17%

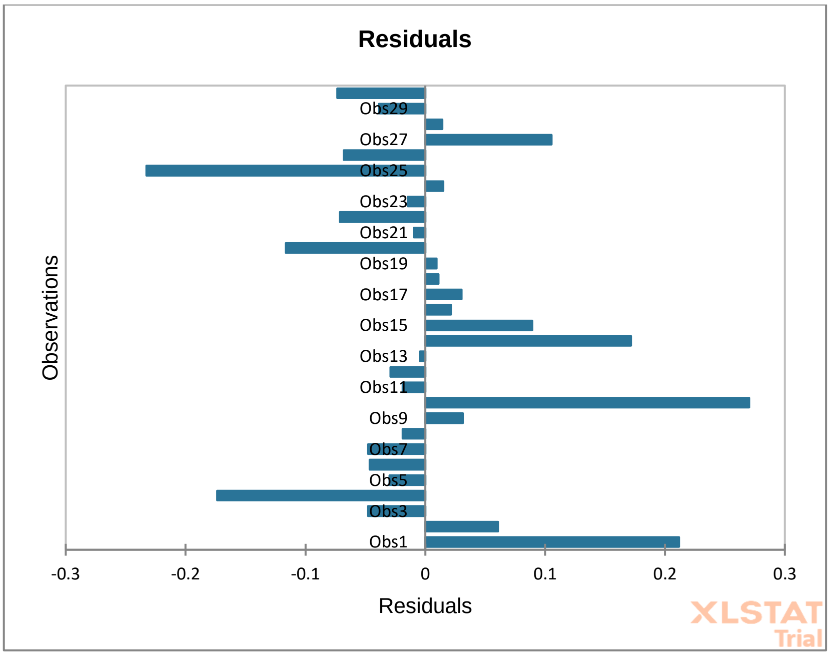


Figure 26: Residuals of non-linear regression predicting change in project duration

The above-mentioned steps are repeated once again using the projects' budget. Where the best fitting non-linear regression equation is also the sin equation resulting in Equation 17. The values of the parameters can be seen in Table 24, where the overall accuracy of the equation is also not expected to be high due to the high standard error and confidence interval. Also, the adjusted R^2 of the regression model is -0.06, where the negative sign indicates an inverse relationship between the variables of the equation. In other words, the model predicts that the higher the category scores, the lower the variation in the project budget and vice versa. In principle, the model's logic is correct however; the low value of the adjusted R^2 indicated high inaccuracy in the model's prediction which cannot be relied on.

Equation 17: Non-linear regression equation predicting percent change in project budget

$$\begin{aligned}\%\ change\ of\ project\ budget \\ &= pr1 + pr2 * \sin(pr3 * X1 + pr4) + pr2 * \sin(pr3 * X2 + pr4) + pr2 \\ &* \sin(pr3 * X3 + pr4) + pr2 * \sin(pr3 * X4 + pr4) + pr2 * \sin(pr3 * X5 \\ &+ pr4) + pr2 * \sin(pr3 * X6 + pr4)\end{aligned}$$

Table 24: Parameters of non-linear equation predicting percent change in project budget

Parameters	Value	Standard error	Lower bound (95%)	Upper bound (95%)
pr1	0.013	0.021	-0.030	0.057
pr2	-0.020	0.012	-0.044	0.005
pr3	1.168	0.183	0.791	1.544
pr4	-0.263	1.962	-4.296	3.770

The results of the regression analysis are shown in Table 25, where it is seen that the predicted percent change in budget is not of high accuracy. Although the predicted results were far off from the actual percent change of the project budget, the error is prediction, though still not acceptable, was not as high as the error in the equation predicting project duration. In fact, the highest residual is 27% and the mean absolute error 117% which is still very high. The residuals can be graphically visualized from Figure 27. Since the outcome of the non-linear regression is not accurate, it is rejected and therefore will not be taken as basis for the prediction model. Hence, other machine learning algorithms were studied in further attempts to reach high levels of accuracy.

Table 25: Prediction results of non-linear regression for percent change in project budget

Planned budget (EGP)	Forecasted budget (EGP)	Percent change in project budget	Predicted change in project budget	Residual
2,500,000,000	3,000,000,000	20%	-1%	21%
1,400,000,000	1,500,000,000	7%	1%	6%
796,000,000	784,000,000	-2%	3%	-5%
1,400,000,000	1,200,000,000	-14%	3%	-17%
54,000,000,000	54,000,000,000	0%	3%	-3%
15,000,000	15,000,000	0%	5%	-5%
796,000,000	784,000,000	-2%	3%	-5%
61,500,000	63,200,000	3%	5%	-2%
4,000,000,000	4,250,000,000	6%	3%	3%
56,906,869	76,923,090	35%	8%	27%
171,219,014	170,681,089	0%	2%	-2%
128,000,000	118,000,000	-8%	-5%	-3%
46,000,000	46,200,000	0%	1%	0%
120,000,000	145,000,000	21%	4%	17%
85,000,000	100,000,000	18%	9%	9%
86,387,391	86,986,132	1%	-1%	2%
138,278,978	145,236,506	5%	2%	3%
850,000,000	876,387,200	3%	2%	1%
4,708,000,000	4,708,000,000	0%	-1%	1%

50,000,000	46,000,000	-8%	4%	-12%
1,000,000,000	1,012,000,000	1%	2%	-1%
8,000,000,000	7,820,000,000	-2%	5%	-7%
56,000,000	61,000,000	9%	10%	-1%
188,000,000,000	190,356,000,000	1.3%	0%	2%
1,600,000,000	1,305,000,000	-18%	5%	-23%
15,000,000	14,000,000	-7%	0%	-7%
7,816,000,000	8,600,000,000	10%	0%	11%
6,480,000,000	6,480,000,000	0%	-1%	1%
108,000,000	103,000,000	-5%	-1%	-4%
1,900,000,000	1,840,000,000	-3%	4%	-7%

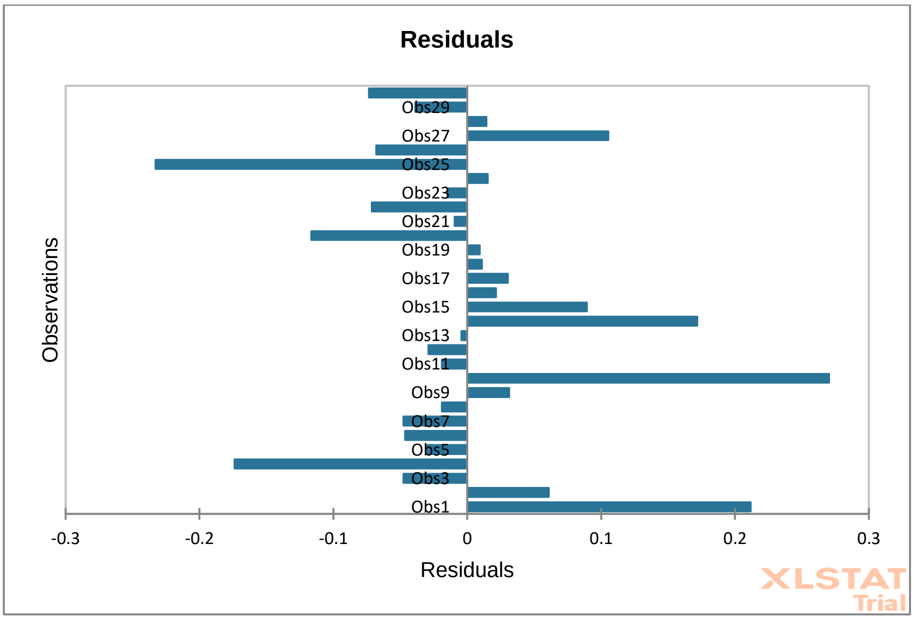


Figure 27: Residuals of non-linear regression predicting change in project budget

5.2.1.3. Numerical Neural Networks

Numerical neural networks, a predictive data analysis tool, was utilized in an attempt to predict project performance through using the calculated scores. The network architecture consisted of six input nodes, one hidden layer with six nodes and an output node. Since the aim was to predict project duration and cost, two neural networks were made. The input nodes of the neural networks were fed with the six category scores and the output nodes generated the predicted project duration in weeks and the project budget in Egyptian pounds. The two predictive neural networks for project duration and budget can be seen in Figure 28 and Figure 29 respectively.

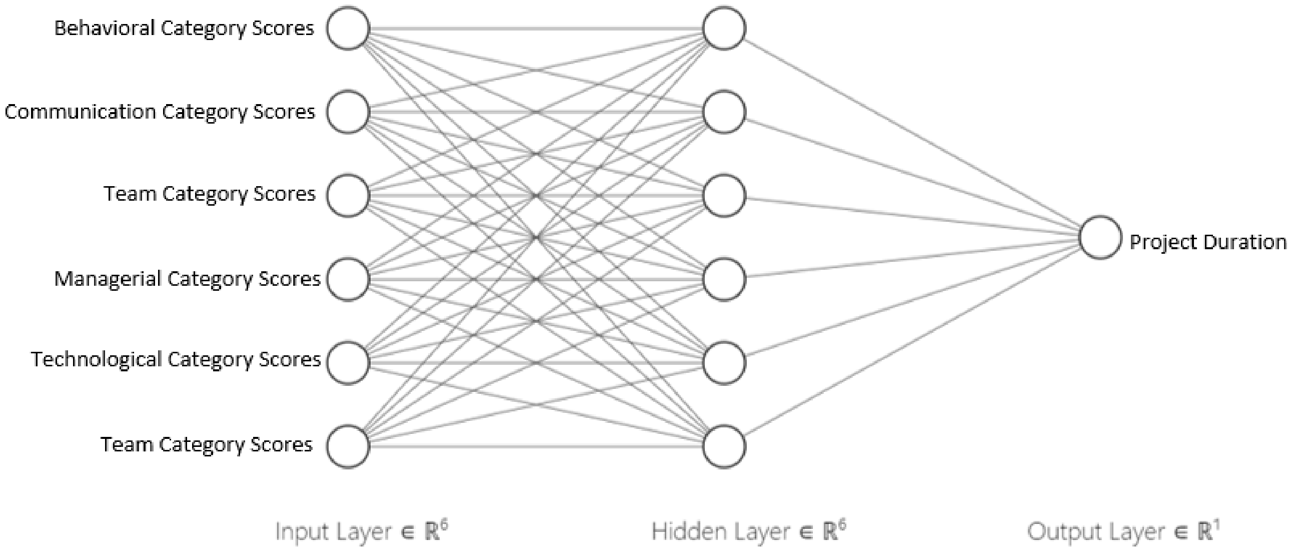


Figure 28: Numerical neural network predicting project duration

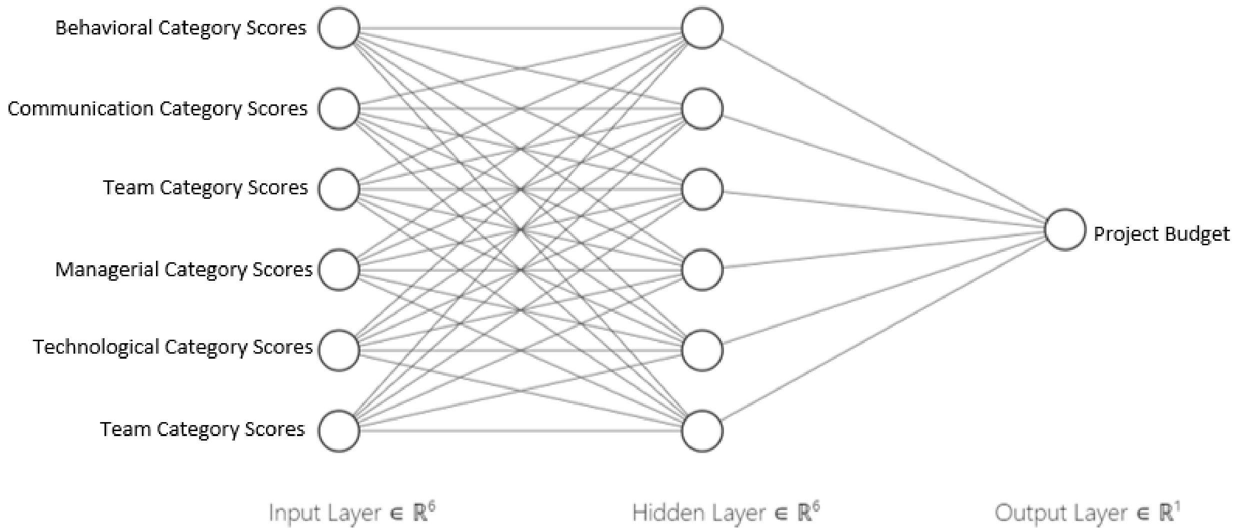


Figure 29: Numerical neural network predicting project budget

Excel add-in NeuralTools (Palisade, 2021) was used in building the neural network algorithm. Where the data was separated into two segments, training dataset and testing dataset. The aim of data separation was to train the neural network algorithm on 80% of the data and examine the accuracy of the network's prediction on the remaining 20% through the testing dataset. The measure of accuracy of the neural network depended on the precision of the predicted duration and budget. The testing dataset results of the neural network predicting project duration can be seen in Table 26. As observed, four out of five predictions were classified by NeuralTools as "Good". Upon initial inspection, the predicted durations seemed to be somewhat close to the actual durations of the projects. However, the testing dataset results of the neural network predicting project budget in Table 27 had large errors in predictions and all predictions made were classified as "Bad" for all testing data. Hence, numerically predicting project performance through neural networks proved to yield an unsuccessful outcome.

Table 26: Numerical neural network prediction project duration results

Actual/forecasted duration (weeks)	Tag Used	Good/Bad	Residual
205	test	Good	-1.57
12	test	Bad	-164.53
286	test	Good	69.47
182	test	Good	-27.33
189	test	Good	-30.53

Table 27: Numerical neural network prediction project budget results

Actual/forecasted Budget (EGP)	Tag Used	Good/Bad	Residual
1,305,000,000	test	Bad	(12,186,080,701)
14,000,000	test	Bad	(13,495,080,701)
8,600,000,000	test	Bad	(4,873,080,701)
6,480,000,000	test	Bad	(6,939,080,701)
103,000,000	test	Bad	(13,307,080,701)

5.2.2. Categorical Analysis

It was proven through numerical analysis that the dataset herein has a complex intertwined pattern making it difficult to establish an algorithm that is able to accurately predict project performance due to the small size of the dataset compared to the number of inputs. This provoked a change in the data analysis approach from numerical analysis to categorical analysis; at which the dependent variables are now categories rather than numbers. Therefore, other machine learning algorithms were resorted to in an effort to create a model that can find a correlation between lean factors and project performance through categorical classification. Considering that the evaluation model would classify the data based on categories, the established categorization has to be fully indicative of the project's status. Therefore, the projects were categorized based on their performance in terms of schedule and budget. In order to be able to correctly categorize the existing data, global statistics on the performance of construction projects were used as reference. According to Assaad et al. (2020), a minor proportion of only 25% of construction projects are performed within 10% of their original planned durations. Hence, projects with a schedule variance of 10% or less were categorized to have a minor delay, projects between 10% to 25% were within the average delay rates and the ones exceeding 25% were considered to have a major delay. According to this breakdown, the data distribution came as shown in Figure 30.

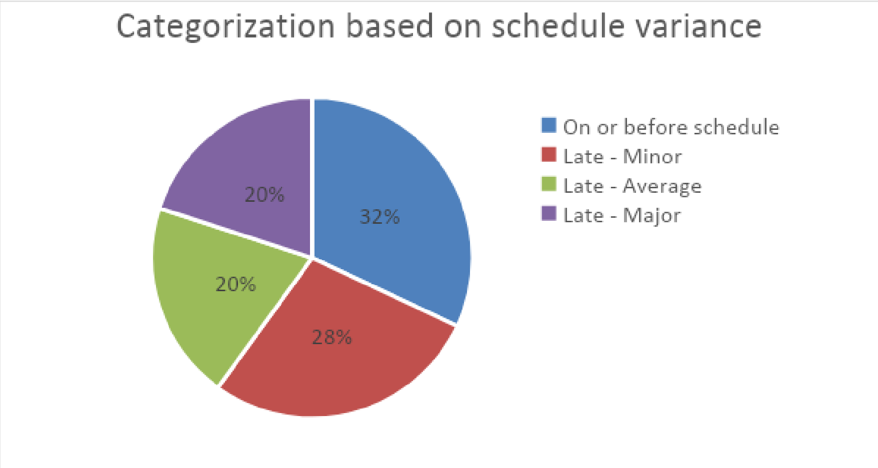


Figure 30: Data distribution based on schedule variance

On the other hand, the average construction project is completed with a 28% budget overrun (Aljohani, 2017). Thus, projects with a budget variance of 28% should be categorized as moderately above budget; however, since there weren't enough data above 28% to represent major overrun, it was reduced to 20% for better representation of all categories. Therefore, the categorization was as follows: projects with a variance of 5% or less were considered minor, projects between 5% to 20% were average and the ones exceeding 20% were major. This resulted in the data distribution shown in Figure 31.

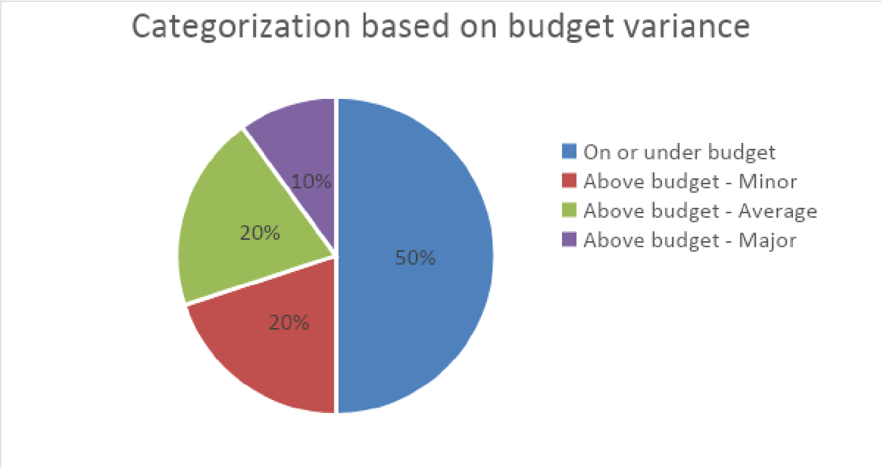


Figure 31: Data distribution based on budget variance

The established categorization pattern not only allows for a deeper understanding of the data but also aids to the credibility of the evaluation model. This is due to the fact that the model will be able to predict, through machine learning algorithms, future projects' performance up to a detailed level of information. Therefore, the key to ensure the credibility of the model was to guarantee that the predictive analysis has very high accuracy and almost no miss-classification. Accordingly, based on the literature review and given that the data were divided into categories, two supervised machine learning algorithms were utilized; decision trees and neural networks.

5.2.2.1. Decision Trees

After categorizing the data, excel add-in XLSTAT (Addinsoft, 2020) was used to perform machine learning algorithms; namely decision trees. Since the evaluation model's outcome will include a predicted categorization of schedule and budget performance, two decision tree models were done to cover both aspects. To start off, the data were separated into two sub-sets, a training set and a validation set. The training set is to train the model on the existing data and the validation set is to test the trained model. The aim of the validation set is to see if the model will correctly predict the classification of new data entries and evaluate how well trained the model is. It goes without saying that as the accuracy of the decision tree model rises, so does the confidence level of the evaluation model, since it increases the chances of precisely predicting project performance. The input data for the decision trees consisted of the six lean category scores along with the project's categorization for schedule and budget. Numerical values were assigned to the schedule and budget categories according to Table 28 and Table 29 in order for the model to run.

Table 28: Numerical values for schedule categories

Numerical value	Category
1	On or before schedule
2	Late - Minor
3	Late - Average
4	Late - Major

Table 29: Numerical values for budget categories

Numerical value	Category
1	On or under budget
2	Above budget - Minor
3	Above budget - Average
4	Above budget - Major

In an effort to verify that the model was trained effectively, the data were separated based on 80-20 proportions. That is, 80% of the data were used as the training set and 20% were used as the validation set. To guarantee that the validation process is unbiased, a set of five projects containing one project representing each of the four established categories along with one random project was done. This ensures that the model is validated with respect to all possible cases for both schedule and budget categories. Moreover, in order to further validate the decision tree, the data of three hypothetical projects each representing the performance of imaginary companies were inserted into the model. The projects embody different performance level scenarios. The first one being the "perfect" performance, where the company is theoretically implementing all of the 27 identified lean factors frequently in the project. In other words, its total score would be 100; therefore, it should be on time and on budget. This would mean that the decision tree will classify this project as 1 indicating on or before schedule and on or under budget. The second scenario represents the "above average" company performance, where there is systematic implementation of lean factors in the project. This level of performance would also mean that the project should be on schedule and budget or, at maximum, slightly beyond one or both. Hence, a classification of 1 or 2 (Late - Minor and Above budget - Minor) is expected of the decision tree. The third project exemplifies "poor" performance, where lean factors are employed very rarely. Consequently, making the project Late - Major and Above budget – Major and therefore should be classified by the decision tree as 4.

The validation process first started out with calculating the category scores for each of the three scenarios. This was done with reference to the lean factors Likert scale in Table 11. Accordingly, the "perfect" performing project was assigned a value of five, leading to a total score of 100. The "above average" project was assigned a value of four for a total of 75 points. Lastly, the "poor" performing project was assigned a value of one, which gave a total score of zero. Then, the data was entered into the decision tree.

The resulting decision tree models for schedule and budget classification are shown in appendix A. Assessing the accuracy of the decision trees depended mainly on the results of the confusion matrix for both the training and validation data sets. The confusion matrix displays how the data is originally classified versus how the decision tree algorithm classified it. The more often the model classifies data correctly, the better accuracy it yields and the more reliable the decision tree becomes. When looking at the confusion matrix for the schedule performance training data set in Table 30 , one can notice that the model was able to correctly classify 17 projects out of the total input of 25 projects. Consequently, the overall accuracy of the decision tree was 68%.

Table 30: Confusion matrix for predicting schedule performance - training data set

from \ to	1	2	3	4	Total	% Accuracy
1	4	1	1	2	8	50.0
2	0	6	1	0	7	85.7
3	0	1	4	0	5	80.0
4	0	0	2	3	5	60.0
Total	4	8	8	5	25	68.0

Meanwhile, the schedule performance validation dataset, shown in Table 31, had an overall accuracy of 50%, which is four projects out of eight. When taking a deeper look into the matrices, the correct classification percentage for all categories does not fall below 50%. This indicates that the overall accuracy of the model is acceptable though it is not very high, which is further reaffirmed with its ability to correctly categorize 63% of the projects - a total of 21 out of 33 projects.

Table 31: Confusion matrix for predicting schedule performance - validation data set

from \ to	1	2	3	4	Total	% Accuracy
1	1	0	1	1	3	66.6
2	0	1	0	0	1	100.0
3	0	1	1	0	2	50.0
4	1	0	0	1	2	50.0
Total	2	2	2	2	8	50.0

As for the decision tree predicting budget performance, the confusion matrix for the training data set and validation data set shown in Table 32 and Table 33 gave a total accuracy of 84% and 62% respectively. Looking at the complete picture, the model predicting budget performance had a higher accuracy than the one predicting schedule performance, as the total correctly classified data was 26 out of 33 projects making the model 78% accurate.

Table 32: Confusion matrix for predicting budget performance - training data set

from \ to	1	2	3	4	Total	% Accuracy
1	12	0	0	1	13	92.3
2	0	5	0	0	5	100.0
3	1	2	2	0	5	40.0
4	0	0	0	2	2	100.0
Total	13	7	2	3	25	84.0

Table 33: Confusion matrix for budget performance - validation data set

from \ to	1	2	3	4	Total	% Accuracy
1	2	2	0	0	4	50.0
2	0	1	0	1	2	50.0
3	0	0	1	0	1	100.0
4	0	0	0	1	1	100.0
Total	2	3	1	2	8	62.0

Despite the fact that the results attained were not of high precision, they were far better than the ones achieved through linear and non-linear regression. Thus, while the achieved outcomes were not satisfactory to reach a finalized method that is ready for use in the evaluation model, the initial results of using machine learning algorithms showed a promising lead to reaching an accurate model. This led to further exploring other methods, like neural networks, that can provide more accurate predictions.

5.2.2.2. Multiclass Classification Neural Networks

- Network Architecture:

R Studio, a statistical computing software, was used to conduct a multi-class classification neural network (R Core Team, 2019). Going with the same approach as the one used in the numerical neural networks; two separate neural network models were created; one predicting schedule performance and the other predicting budget performance. The input layer was identical for both the schedule and budget networks; it consisted of 6 input nodes, each node representing one of the six lean category scores. The output layer in each network consisted of 4 nodes, one for each category of projects in schedule and budget performance as illustrated in Figure 32. Since the R Studio package "NeuralNetTools" could compute categories in a text format, the categories were kept with their original names (Beck MW,2018). The aim of using neural networks was to reach a simple algorithm that predicts project performance with the minimum error percentage. Hence, multiple iterations were conducted to reach the minimum number of hidden layers and nodes that provide the least classification error.

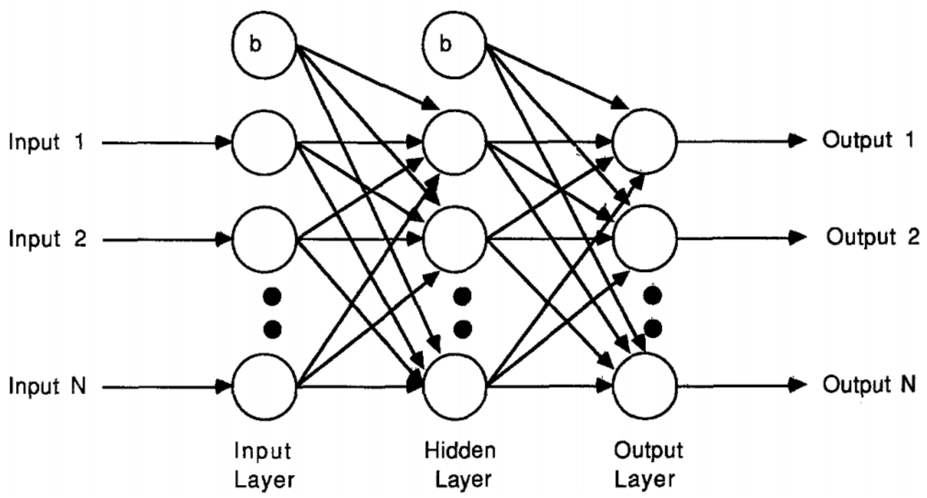


Figure 32: Neural networks architecture (Williams, 1994)

- Multiclass neural networks calculation method:

Classification neural networks are calculated through a series of feedforward steps, were the data moves in a horizontal direction from the input node all the way to the output node. Figure 33 explains how information flows through the network. Where $I_{1 \ldots 6}$ are the input nodes, each having one of the six lean category scores, $H_{1 \ldots 6}$ are the nodes in the hidden layer and $O_{1 \ldots 4}$ are the output nodes (representing one of the four established categories for either schedule or budget performance).

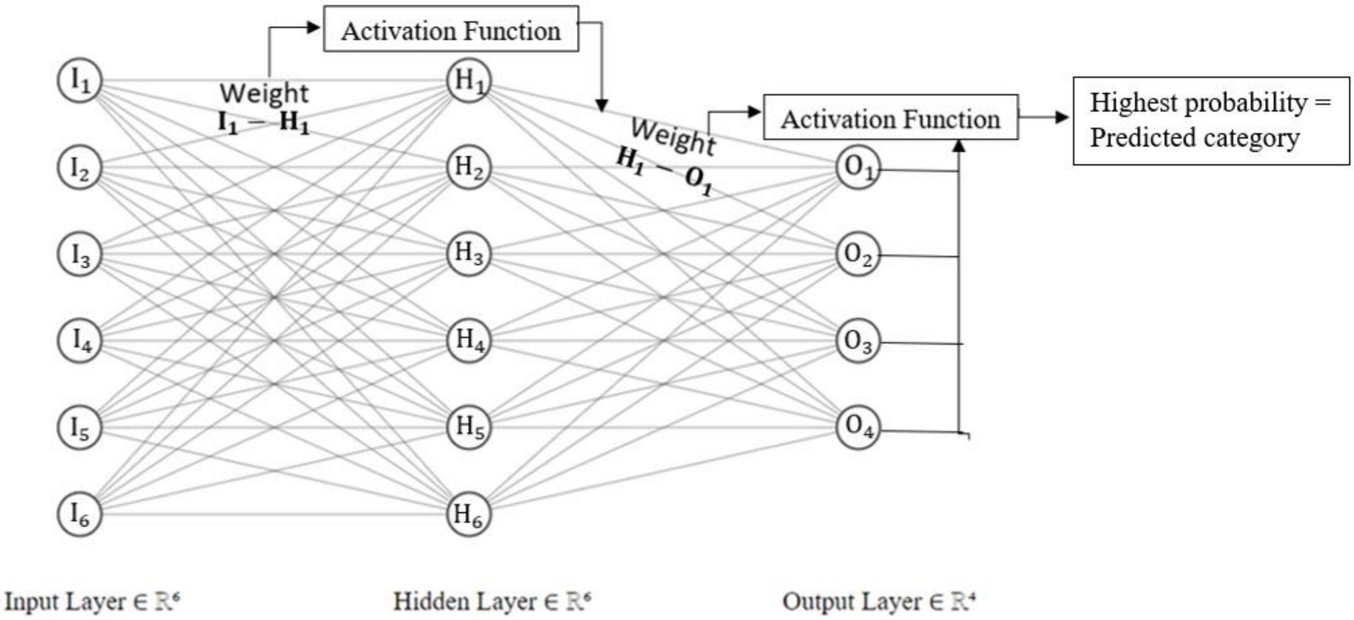


Figure 33: Information flow through a multiclass neural network

To illustrate the calculation process, take the path of nodes I_1 , H_1 and O_1as an example:

1) The input layer value of I_1 is multiplied by the weight $I_1 - H_1$ where this weight is automatically calculated by the software.

2) Then, the result of this multiplication is added to a bias value of 1.

3) The resulting number is then activated by passing through the activation function, in this case, the Sigmoid function. This function, shown in Equation 18, takes the input value and turns it into a value between 0 and 1 representing the predicted probability of a certain event happening. The output value of the activation function transfers information from the left side of the hidden layer to its right side.

Equation 18: Sigmoid function

$$S(x) = \frac{1}{1+ e^{-x}}$$

4) The input value for H_1 becomes the same as the output value calculated by the activation function. This value is then multiplied by the weight $H_1 - O_1$ and the result is added to a bias value of 1.

5) The result is activated by the sigmoid function again giving a probability.

6) The above steps are repeated for all the nodes in the network ($I_{1....6}$, $H_{1...6}$ and $O_{1...4}$).

7) This results in having four final predicted probability values, each presenting the chance of the project belonging to a certain category.

8) The output node with the highest probability is the final predicted categorization of the project.

- Multiclass classification neural network predicting schedule performance:

The R Studio code for the neural network predicting schedule performance is shown in Figure 34 below:

```
library(nnet)
library(NeuralNetTools)
# Read Data
getwd()
data <-read.csv("Multi classification neural network - sched.csv",header = TRUE)
str(data)
summary(data)

getwd()
datatest <-read.csv("test data.csv",header = TRUE)
str(datatest)
summary(datatest)

#fit model

fit <- nnet(Status~.,data=data, size =6, decay= 0.0001, maxit = 500)
neuralweights(fit)
plotnet(fit)
#predictions
predictions <- predict(fit, data[,1:6], type = "class")
list(predictions)
list(data$Status)
#predicting tests
predictiontest <-predict(fit, datatest[,1:6], type = "class")
list(predictiontest)

library(caret)
confusionMatrix(as.factor(predictions), as.factor(data$Status))
```

Figure 34: R code predicting schedule performance

Given the aforementioned calculation method, the main indicator of the efficiency of the network lies in the model's ability to calculate weights that adequately predict projects' categories. Accordingly, when building the network, the main aim was to find the model that gives the least error. To do this, multiple iterations were done to reach the optimum result, which is reaching the minimum classification error using the least number of hidden layers and nodes.

After a series of iterations, the code generated the network shown in Figure 35. As seen, the final optimum neural network predicting schedule performance consisted of one hidden layer with six nodes. The neural network weights are also shown in Table 34.

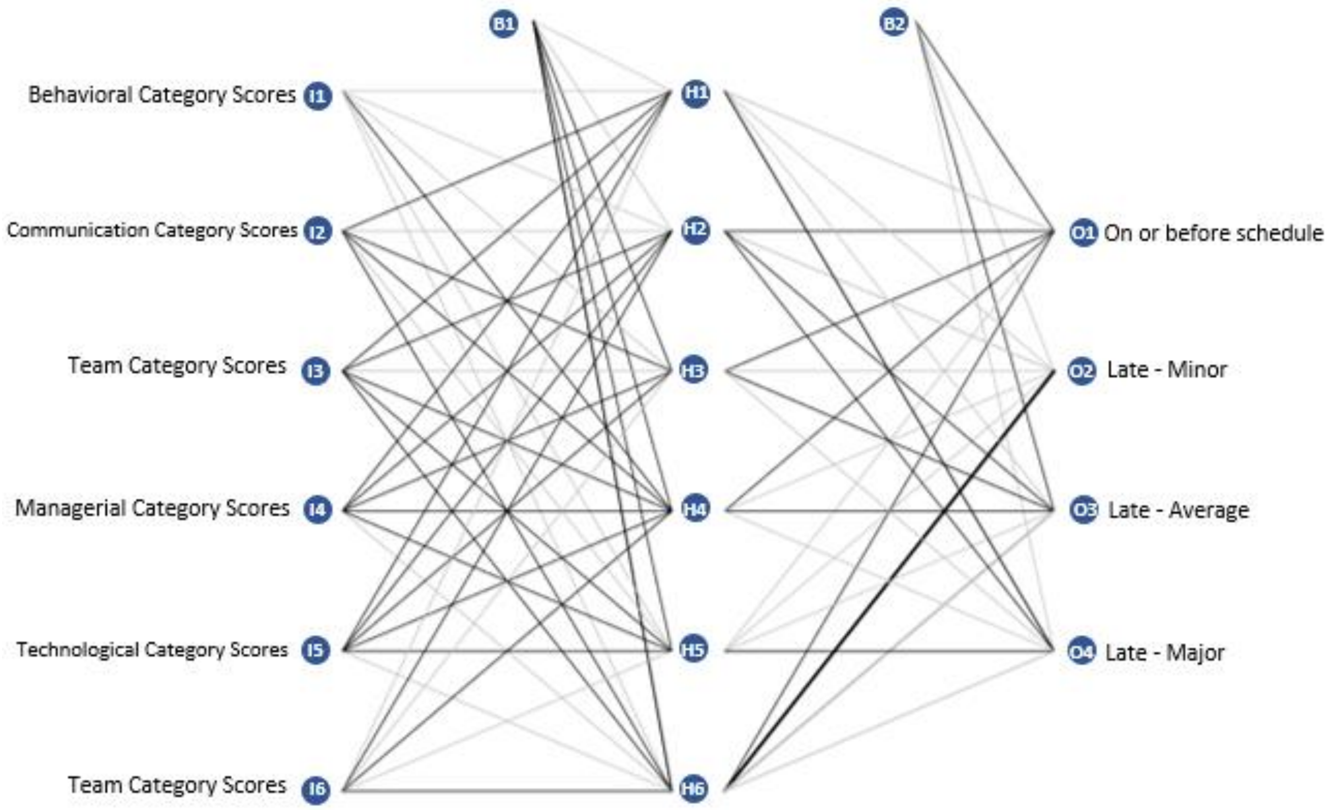


Figure 35: Multiclass neural network predicting schedule performance

Table 34: Node weights of multiclass classification neural network predicting project schedule performance

	B	I1	I2	I3	I4	I5	I6
Input Layer	1.000	6.696	4.226	9.486	7.600	9.193	6.745
Weights between input and hidden layer	B	I1	I2	I3	I4	I5	I6
H1	-12.008	0.239	-3.048	-2.819	9.582	4.813	-6.187
H2	11.225	0.182	-8.555	4.219	-3.433	-4.056	8.459
H3	-7.301	3.809	-4.130	-1.126	-4.265	0.421	6.118
H4	-0.481	0.259	-4.322	-5.242	4.990	0.573	2.155
H5	0.000	0.344	0.041	0.166	0.133	0.513	0.180
H6	0.032	-0.152	-0.084	-0.095	-0.040	-0.103	-0.116
	B	H1	H2	H3	H4	H5	H6
Values (Z)		25.300	9.988	2.797	-9.012	10.991	-4.271
Sigmoid of Z	1.000	1.000	1.000	0.943	0.000	1.000	0.014
Weights between hidden and output layer	B	H1	H2	H3	H4	H5	H6
O1	-4.290	-4.078	18.243	1.498	-8.807	-2.431	0.006
O2	4.929	-21.463	8.967	3.215	-23.288	2.624	-0.049
O3	2.408	14.390	-1.759	-11.105	5.620	0.768	0.008
O4	-3.060	11.272	-25.576	6.302	26.532	-0.960	0.012

The aforementioned neural network automatically generated the confusion matrix shown in Table 35. The network assessment depended on the confusion matrix that the code generated, where the matrix showed that the model was able to correctly classify 24 out of the 25 training projects. This makes the overall accuracy of the model to be 96%. Such accurate results mean that the neural network algorithm was not only able to find a correlation between the lean category scores and project schedule performance, but also it was able to map this relationship and train itself to correctly classify projects based on that relationship. When looking at the misclassified project, one can find that its original classification was "On or before schedule" however, the network predicted it to be classified as "late – Minor". Although this is a misclassification, the predicted classification was not too far off from the original one. Hence, the results of this network are deemed acceptable to use in the evaluation model since they have low chance of error due to the model's high accuracy.

Table 35: Confusion matrix for multiclass neural network predicting schedule performance – training data set

from \ to	1	2	3	4	Total	% Accuracy
1	7	0	0	0	7	100.0
2	1	6	0	0	7	85.8
3	0	0	6	0	6	100.0
4	0	0	0	5	5	100.0
Total	8	6	6	5	25	96.0

As a final step before finalizing the evaluation model, the established multiclass classification neural networks were validated. New testing data were introduced to validate that the neural networks are efficient and will yield realistic results when incorporated in the evaluation model. In order to do that, the same eight projects that were used in the validation of the decision tree were also used in the validation of the multiclass neural network. That is, a set of five projects containing one project representing each of the four established categories along with one random project. Moreover, a project representing a company that frequently implements the 27 identified lean factors therefore, it should be on time and on budget. Another project representing a company that regularly implements the lean factors, leading to high probability of the project to be on schedule and budget. Lastly, a company that employs lean factors very rarely making the project delayed and above budget.

The category scores for each of the three scenarios were compiled in a single source and were incorporated in the R Studio neural network code as test data. The network was then programmed to predict the classification of the projects based solely on their category scores. The predicted results are shown in Table 36. As displayed, the neural network was able to correctly classify a 100% of the validation data set including the three hypothetical projects as shown in Figure 36. Making the network 96% accurate as it was able to correctly predict 32 of 33 projects.

Table 36: Confusion matrix for multiclass neural network predicting schedule performance – validation data set

from \ to	**1**	**2**	**3**	**4**	**Total**	**% Accuracy**
1	**3**	**0**	**0**	**0**	**3**	**100.0**
2	**0**	**2**	**0**	**0**	**2**	**100.0**
3	**0**	**0**	**1**	**0**	**1**	**100.0**
4	**0**	**0**	**0**	**2**	**2**	**100.0**
Total	**3**	**2**	**1**	**2**	**8**	**100.0**

```
> #predicting tests
> predictiontest <-predict(fit, datatest[,1:6], type = "class")
> list(predictiontest)
[[1]]
[1] "On or before schedule" "On or before schedule" "Late - Major"
```

Figure 36: Schedule performance prediction for validation dataset

- Multiclass classification neural network predicting budget

performance:

The R Studio code for the neural network predicting budget performance is shown in Figure 37 below:

```
library(nnet)
library(NeuralNetTools)
# Read Data
getwd()
data <-read.csv("Multi classification neural network - cost.csv",header = TRUE)
str(data)
summary(data)
# read data
getwd()
datatest <-read.csv("test data.csv",header = TRUE)
str(datatest)
summary(datatest)

#fit model

fit <- nnet(Status~.,data=data, size =4, decay= 0.0001, maxit = 500)
neuralweights(fit)
plotnet(fit)
#predictions
predictions <- predict(fit, data[,1:6], type = "class")
list(predictions)
list(data$Status)
#predicting tests
predictiontest <-predict(fit, datatest[,1:6], type = "class")
list(predictiontest)

library(caret)
confusionMatrix(as.factor(predictions), as.factor(data$Status))
```

Figure 37: R Code predicting budget performance

In an effort to optimize and simplify the network, iteration steps were done in order to find the minimum number of hidden layers and nodes. Figure 38 shows the network that yielded results with the highest accuracy. As shown, it consisted of one hidden layer with four nodes, the node weights can be seen in Table 37.

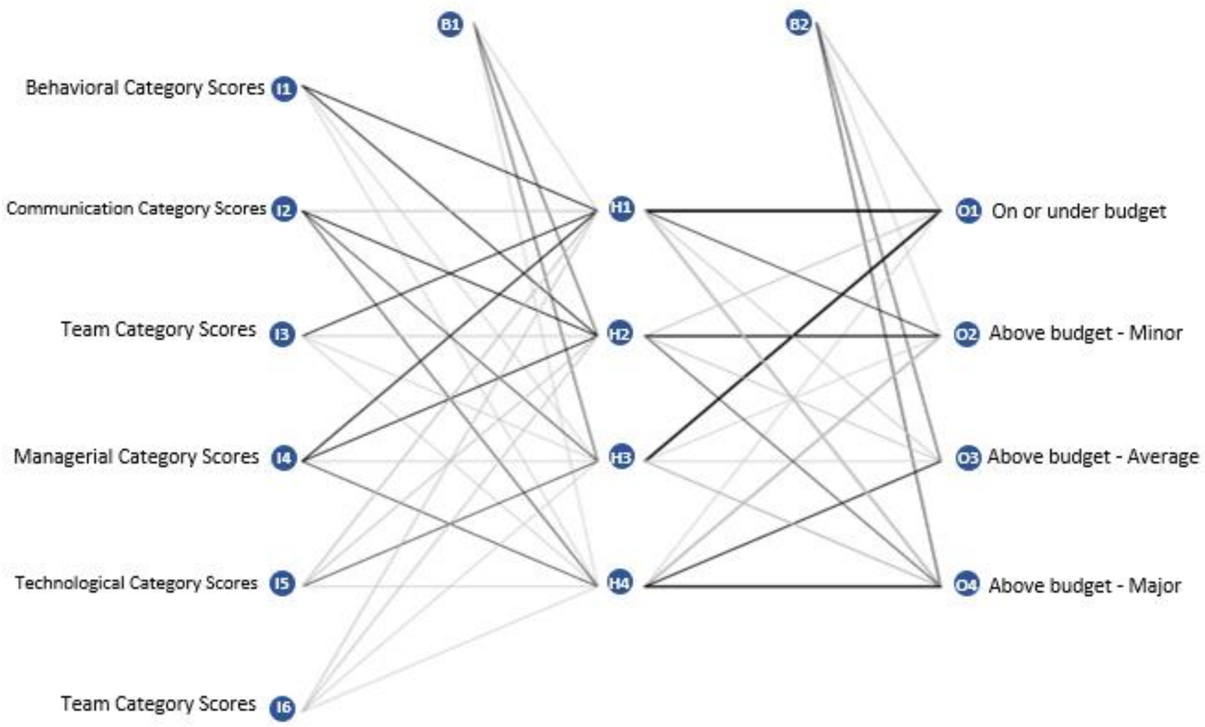


Figure 38: Multiclass neural network predicting budget performance

Table 37: Node weights of multiclass classification neural network predicting project budget performance

	B	I1	I2	I3	I4	I5	I6
Input Layer	1	6.696	4.226	9.486	7.600	9.193	6.745
Weights between input and hidden layer	B	I1	I2	I3	I4	I5	I6
H1	-18.114	-7.718	4.011	15.604	-6.248	-0.582	-1.006
H2	-1.293	-5.484	-5.091	-0.951	1.075	-0.540	7.425
H3	-10.839	1.593	14.023	-2.759	-1.100	-4.803	-2.657
H4	4.516	10.561	-6.603	-7.410	8.321	-9.687	2.488
	B	H1	H2	H3	H4		
Values (Z)		35.568	-15.253	-37.506	-32.007		
Sigmoid of Z	1	1.000	0.000	0.000	0.000		
Weights between hidden and output layer	B	H1	H2	H3	H4		
O1	-27.784	42.103	10.602	-18.104	30.748		
O2	19.192	-31.917	-12.579	9.142	-4.835		
O3	1.990	8.782	-1.246	-7.785	9.268		
O4	6.563	-18.998	3.190	16.792	-35.234		

The results of the neural network were satisfactory as seen from the automatically generated confusion matrix in Table 38. The model had 92% accuracy as there were only two misclassified projects. These projects were originally classified as “above budget – minor”, however, they were predicted to be “on or under budget”. Once more, the difference between the original categories and the predicted ones was not far-fetched providing an acceptable error. Therefore, given the high accuracy of the network, it is considered fit for use in the evaluation model.

Table 38: Confusion matrix for multiclass neural network predicting budget performance – training data set

from \ to	1	2	3	4	Total	% Accuracy
1	**13**	**2**	**0**	**0**	**15**	**86.6**
2	**0**	**3**	**0**	**0**	**3**	**100.0**
3	**0**	**0**	**5**	**0**	**5**	**100.0**
4	**0**	**0**	**0**	**2**	**2**	**100.0**
Total	**13**	**5**	**5**	**2**	**25**	**92.0**

As for the validation data set, as seen in Table 39 the model was able to correctly predict 100% of the validation data set. Figure 39 also shows that the network was able to predict all three of the hypothetical projects. The testing data set along with the validation data set shows that the network is 94% accurate as it was able to correctly predict 31 out of 33 projects.

Table 39: Confusion matrix for multiclass neural network predicting budget performance – validation data set

from \ to	1	2	3	4	Total	% Accuracy
1	**5**	**0**	**0**	**0**	**5**	**100.0**
2	**0**	**1**	**0**	**0**	**1**	**100.0**
3	**0**	**0**	**1**	**0**	**1**	**100.0**
4	**0**	**0**	**0**	**1**	**1**	**100.0**
Total	**3**	**1**	**1**	**1**	**8**	**100.0**

```
> #predicting tests
> predictiontest <-predict(fit, datatest[,1:6], type = "class")
> list(predictiontest)
[[1]]
[1] "On or under budget"   "On or under budget"   "Above budget - Major"
```

Figure 39: Budget performance prediction for validation dataset

As per the above-mentioned results, it is clear that using multiclass classification neural networks to find a correlation between lean category scores and project performance proved to be successful. This accomplishment greatly adds to the legitimacy of the evaluation model where the established neural networks act as a precise database. This solid foundation will consequently raise the probability of correctly predicting performance of new projects. Moreover, the above results not only validate the model but also add to the validity of the neural networks' algorithm as they proved that the established model is effective, accurate and efficient. Thus, raising confidence in the fact that an accurate and precise correlation between category scores and project performance was established. Additionally, the results confirmed that the existing data provide a sufficient source for a stable setup to build the evaluation model. Such solid grounds led to the decision to incorporate the established neural networks in the evaluation model.

5.2.3. *Comparison*

Table 40 shows a comparison between the five different algorithms that were used in developing the performance prediction model predicting schedule performance.

Table 40: Comparison between the different algorithms used to develop the schedule prediction model

Data Analysis method	Algorithm	Set of hyperparameters	Parameter of accuracy	Result	Decision
Numerical	Linear Regression	The six lean category scores	R Squared	0.13	Reject
Numerical	Non-linear Regression	The six lean category scores	Average residual percent	16%	Reject
Numerical	Neural Networks	The six lean category scores	Accuracy of prediction	80%	Reject
Categorical	Decision Trees	The six lean category scores	Percentage of Accuracy	63%	Reject
Categorical	Multiclass Classification Neural Networks	The six lean category scores	Percentage of Accuracy	96%	Accept

Table 41 shows a comparison between the different algorithms that were used in developing the performance prediction model predicting budget performance.

Table 41: Comparison between the different algorithms used to develop the budget prediction model

Data Analysis method	Algorithm	Set of hyperparameters	Parameter of accuracy	Result	Decision
Numerical	Linear Regression	The six lean category scores	R Squared	-0.06	Reject
Numerical	Non-linear Regression	The six lean category scores	Average residual percent	6%	Reject
Numerical	Neural Networks	The six lean category scores	Accuracy of prediction	0%	Reject
Categorical	Decision Trees	The six lean category scores	Percentage of Accuracy	78%	Reject
Categorical	Multiclass Classification Neural Networks	The six lean category scores	Percentage of Accuracy	94%	Accept

Chapter 6. Developing a User-friendly Tool

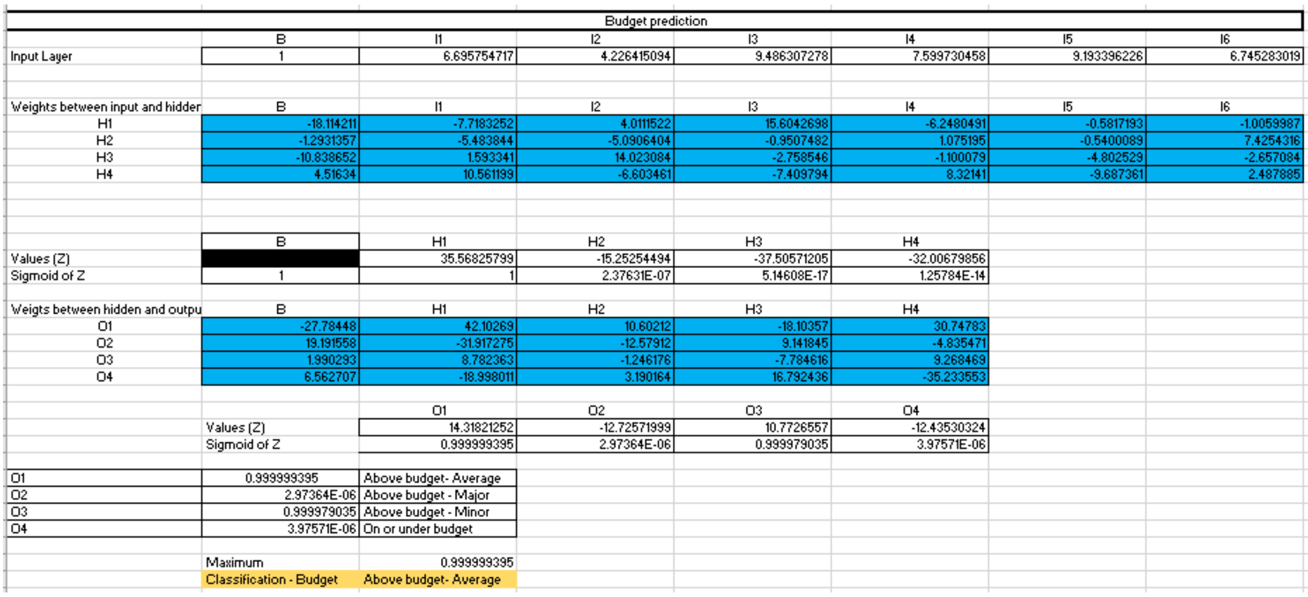
The networks were incorporated in a user-friendly evaluation model that companies can use as a tool to self-evaluate their performance. The evaluation depends on the companies' self-rated performance in the 27 lean factors. The model then takes the user's input, computes the score and, as a final step, predicts the project's performance using the established neural networks. The following process outlines the creation of the model:

1- In the backend of the model, an excel sheet was created to store the user's self-rated input values, here the sheet saves all the answers that the user provides. Based on the responses, the sheet is programmed to calculate the final score out of 100 as per the established scoring system.

2- Neural network weights were retrieved from R Studio to simulate the network on excel. This was done by linking the weights with the user input sheet and computing the network as seen in Figure 40 and Figure 41.

Schedule prediction							
	B	I1	I2	I3	I4	I5	I6
Input Layer	1	6.695754717	4.226415094	9.486307278	7.599730458	9.193396226	6.745283019
Weigts between input and hidden	B	I1	I2	I3	I4	I5	I6
H1	-12.007652	0.2392432	-3.0484692	-2.8191326	9.5824025	4.8125393	-6.1871138
H2	11.2252935	0.1822619	-8.5547097	4.2190764	-3.4332342	-4.0563633	8.4590188
H3	-7.3008535	3.8094899	-4.1298881	-1.1255886	-4.2646487	0.4206776	6.1176659
H4	-0.481411	0.2589064	-4.3222	-5.2418819	4.989694	0.5733668	2.1552899
H5	-0.000266872	0.343733391	0.040745387	0.165852216	0.133353876	0.512950638	0.180092598
H6	0.03160333	-0.15177901	-0.08391142	-0.09466706	-0.0403648	-0.10306977	-0.11557149
	B	H1	H2	H3	H4	H5	H6
Values (Z)		25.30043057	9.988441724	2.796918887	-9.01179298	10.99080712	-4.271242248
Sigmoid of Z	1	1	0.999954074	0.942509099	0.000121948	0.999983144	0.013772106
Weights between hidden and outp	B	H1	H2	H3	H4	H5	H6
O1	-4.2895879	-4.07787299	18.24273435	1.49815595	-8.80704234	-2.43063672	0.00550652
O2	4.92874122	-21.46252535	8.96691622	3.21456308	-23.28769342	2.62395063	-0.04858708
O3	2.407665927	14.39026212	-1.758990328	-11.10547077	5.620206557	0.767643955	0.008169179
O4	-3.06024947	11.27172827	-25.57595023	6.3021315	26.53225917	-0.95974114	0.01199119
		O1	O2	O3	O4		
	Values (Z)	8.854867351	-1.917127403	5.340440138	-12.37980482		
	Sigmoid of Z	0.999857335	0.128182241	0.99522911	4.20259E-06		
O1	0.999857335	Late - Average					
O2	0.128182241	Late - Major					
O3	0.99522911	Late - Minor					
O4	4.20259E-06	On or before schedule					
	Maximum	0.999857335					
	Classification - Schedule	Late - Average					

Figure 40: Evaluation model backend - simulating the schedule performance neural network on excel



Budget prediction							
	B	I1	I2	I3	I4	I5	I6
Input Layer	1	6.695754717	4.226415094	9.486307278	7.599730458	9.193396226	6.745283019

Weights between input and hidder	B	I1	I2	I3	I4	I5	I6
H1	-18.114211	-7.7183252	4.0111522	15.6042698	-6.2480491	-0.5817193	-1.0059987
H2	-1.2931357	-5.483844	-5.0906404	-0.9507482	1.075195	-0.5400089	7.4254316
H3	-10.838652	1.593341	14.023084	-2.758546	-1.100079	-4.802529	-2.657084
H4	4.51634	10.561199	-6.603461	-7.409794	8.32141	-9.687361	2.487885

	B	H1	H2	H3	H4
Values (Z)		35.56825799	-15.25254494	-37.50571205	-32.00679856
Sigmoid of Z	1	1	2.37631E-07	5.14608E-17	1.25784E-14

Weigts between hidden and outpu	B	H1	H2	H3	H4
O1	-27.78448	42.10269	10.60212	-18.10357	30.74783
O2	19.191558	-31.917275	-12.57912	9.141845	-4.835471
O3	1.990293	8.782363	-1.246176	-7.784616	9.268469
O4	6.562707	-18.998011	3.190164	16.792436	-35.233553

	O1	O2	O3	O4
Values (Z)	14.31821252	-12.72571999	10.7726557	-12.43530324
Sigmoid of Z	0.999999395	2.97364E-06	0.999979035	3.97571E-06

O1	0.999999395	Above budget- Average
O2	2.97364E-06	Above budget - Major
O3	0.999979035	Above budget - Minor
O4	3.97571E-06	On or under budget
	Maximum	0.999999395
	Classification - Budget	Above budget- Average

Figure 41: Evaluation model backend - simulating the budget performance neural network on excel

3- The user interface was created using excel Visual Basic, where as soon as the evaluation process starts, the user is prompted to fill in questions identical to the ones that were in the project-based survey as seen in Figure 42.

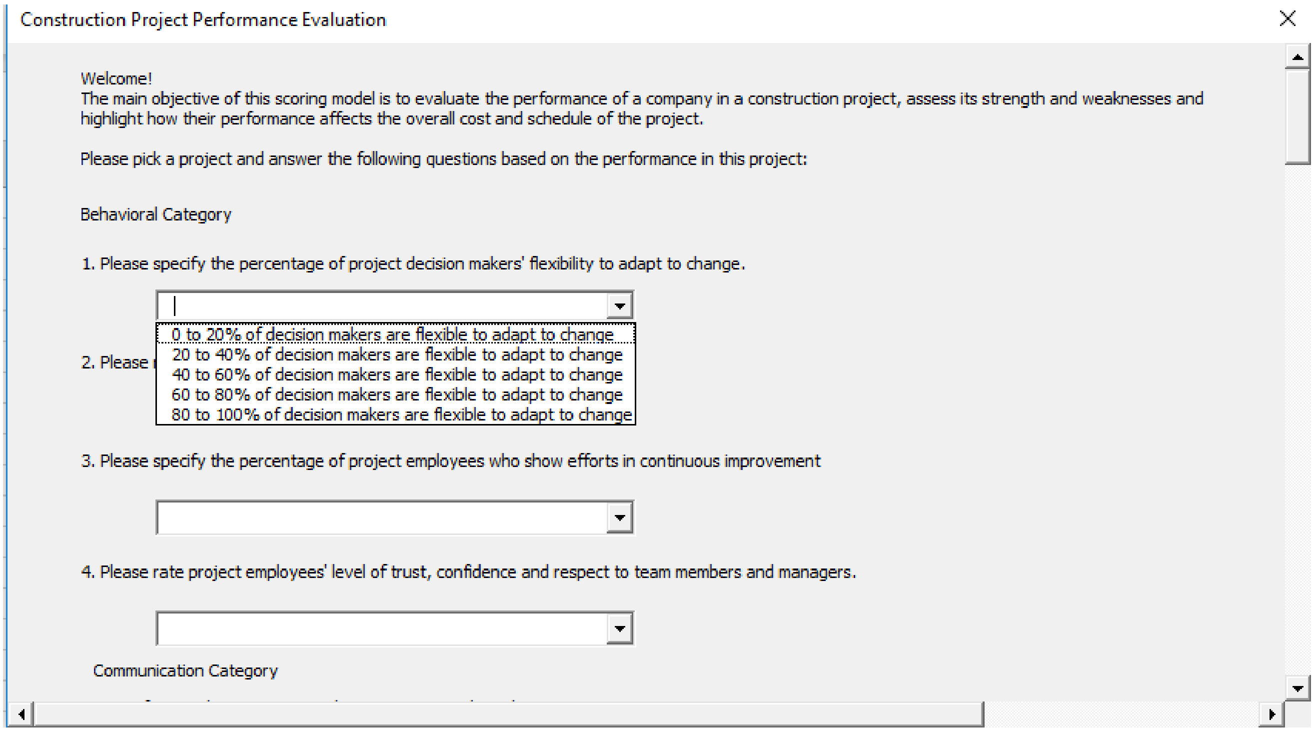


Figure 42: Evaluation model user interface

4- When the user provides answers for all questions in the survey, the results are displayed as seen in Figure 43.

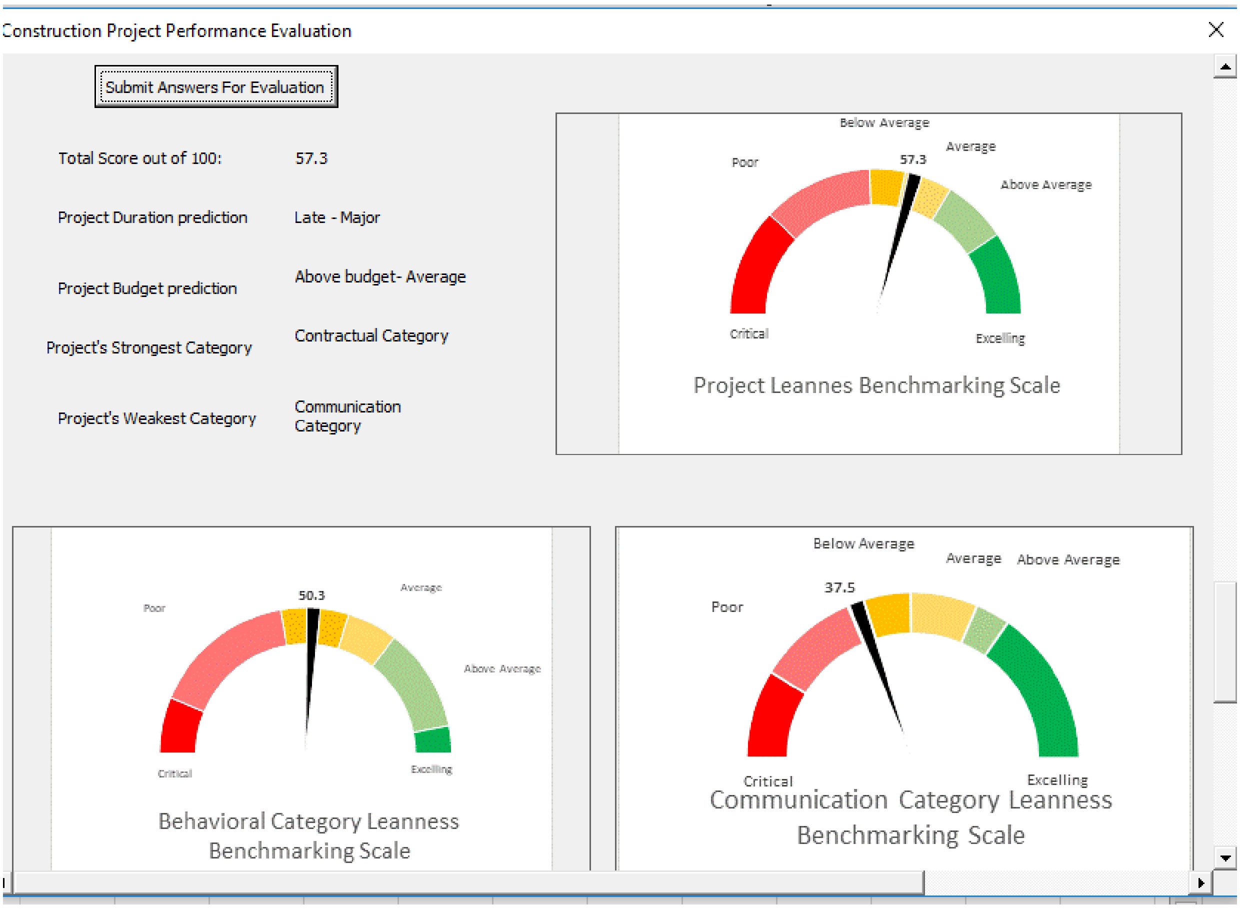


Figure 43: Evaluation model results

The range figure presented on the right side of the user-interface helps companies visualize what their score means. It provides a benchmark of the company's performance as compared to the performance of other companies in the database. Since the range quartiles are separated based on the company scores in the database, users can visually compare their performance to other companies. For example, in the case shown, the company can see that its overall score of 57 is considered average performance as compared to the other companies. This also goes in line with the model's prediction that this project is likely to be Late-Major and Above Budget-Average. The model also produces a set of charts showing the performance of the company in each of the six categories. As seen in Figure 43, the company's weakest category is the communication category, hence the benchmarking scale is highlighting to the user poor performance. On the other hand, the user's strongest performing category is the contractual category scoring 75 out of 100. However, the contractual category leanness benchmarking scale in Figure 44 shows that the company's performance in the contractual category is considered to be the average performance as compared to other companies in the industry. These benchmarking scales report accurately the user's performance status as they show where the company stands as compared to other companies in the field. For this reason, the user's strongest performing category appeared to be only in the average area. This means that compared to other companies, this user needs to set goals to further improve in the contractual category even though it is their strongest category.

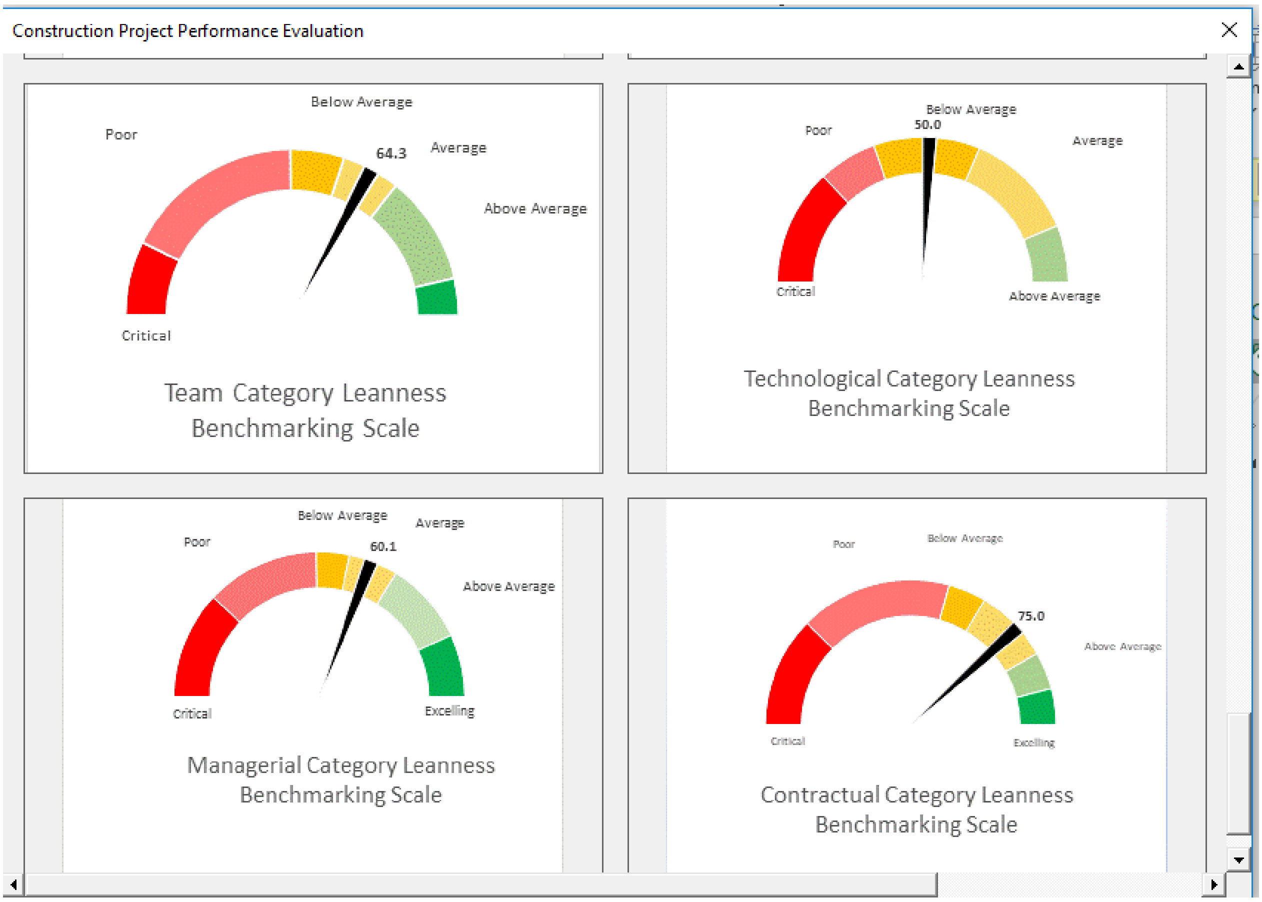


Figure 44: Team, technological, managerial and contractual categories benchmarking scales

It should be noted that the results will not appear unless all questions are answered. If a question was left empty, the user will get a warning message as seen in Figure 45.

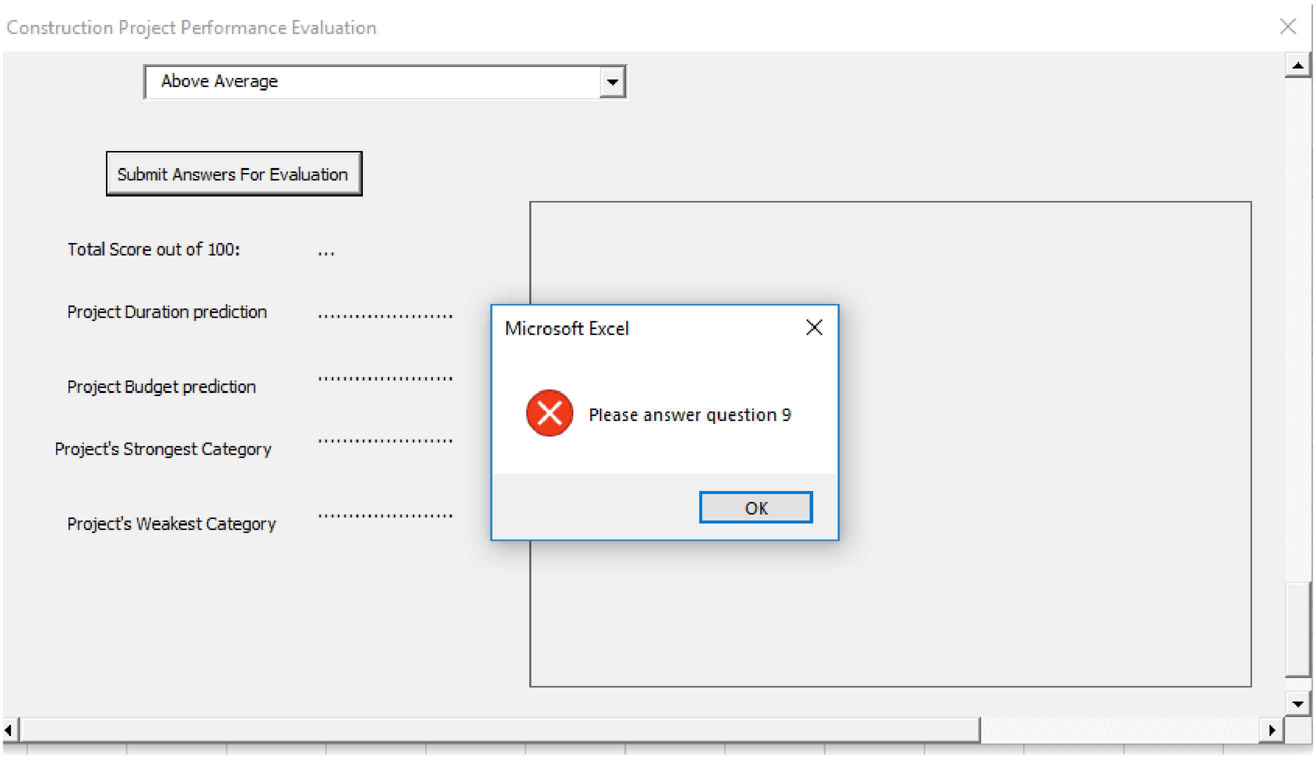


Figure 45: Warning message

Chapter 7. Conclusion

7.1 Summary and Conclusion

Effective implementation of lean construction principles is a great concern for academic researchers and field professionals alike. This growing attention results from the various tangible benefits of applying lean principles and techniques to construction projects. The reviewed literature is extensive when it comes to studying and evaluating the different lean techniques. However, there is a lack of research effort that aims to quantify and evaluate the quality of implementing lean techniques in construction projects. The outcomes of this research contribute to filling such gap through developing an unprecedented scoring method that evaluates the overall quality and frequency of implementing lean techniques in projects. Moreover, it provides a context of the score through benchmarking the project's performance by comparing it to that of other companies in the field; thus, offering a holistic performance evaluation.

To achieve such outcomes, a multistep methodology is followed involving different approaches for data collection and analysis. The initial step is to identify the main lean factors that deem a construction project to be following lean principles. These factors are recognized from the available literature and compiled into a list that is inclusive of all the aspects which lean principles aim to improve in a project. Second, an expert-based survey is created using the established list of lean factors with the aim of determining the relative importance of the identified factors. This is done through collecting experts' opinions by getting them to rate each factor in terms of its overall significance in construction projects. Such information allows for creating a fair and indicative project leanness score that accurately assesses the overall quality and frequency of implementing lean principles in the project. This leads to the third step of the research which is developing a leanness score that takes into consideration the relative importance of each of the lean factors and accordingly precisely measures the overall leanness of the project. Fourth, a project-based survey is created in order to build a database that is inclusive of different types of construction projects. This survey is used to collect information on how the different companies are implementing lean principles in their projects. The responses are then quantified using the established leanness score allowing for the creation of a benchmarking scale that companies can use to compare their performance to that of other companies in the field. The project-based survey responses are also used in the fifth step of the research which is developing a machine learning based model that predicts project performance based on its implementation of lean strategies. In the sixth and final step, the findings of the research are summarized and presented through a user-friendly tool that companies can use to self-rate their project performance. The tool automatically calculates the overall project leanness score and machine learning algorithms use the score to predict and categorizes the project's schedule and budget performance.

To this end, the following is achieved:

1. 27 lean factors that are considered the most influential on construction projects were identified and compiled into a list. Further, the factors are categorized into six categories by topic such as behavioral, communication, team, managerial, technological and contractual categories.

2. An expert-based survey is conducted and responses are collected from a total of 71 experts, 53 of them practicing in USA and 18 practicing in Egypt. The results of the survey dictate the relative importance of the factors based on the opinions of the experts.

3. A comparison is done between experts' opinions in both countries highlighting that there is no significant difference in opinions.

4. Statistical methods are used to develop a leanness scoring system that considers the relative importance of lean factors. This allows for a detailed and reasonable evaluation method that is indicative of the overall quality and frequency of implementing lean factors in a construction project.

5. The leanness score is further broken down into category scores based on the established six categories. These category scores are used to indicate areas of strength and weakness in the project's performance.

6. A project-based survey is conducted and responses from a total of 30 projects are collected. The established leanness and category scoring systems are utilized to quantify the performance of the projects.

7. The database of the leanness and category scores of the 30 projects is used to develop a set benchmarking scales that demonstrate the different levels of overall performance and category performance of companies in the field.

8. Machine learning algorithms, namely multiclass classification neural networks, are

used to predict construction projects performance in terms of schedule and budget. The algorithm's prediction categorizes the project's schedule performance as either on or before schedule, late - minor, late - average or late – major. Similarly, the project's budget performance is categorized as either on or under budget, above budget – minor, above budget – average or above budget – major. Noting that the achieved accuracy of the predicting algorithm is 96% and 94% for the schedule and budget performance respectively.

9. A user-friendly tool is developed allowing companies to self-rate their performance in construction projects. The tool uses the user's input data to automatically calculate the leanness score based on the established scoring method. Additionally, it calculates the six categories' scores and highlights areas of strength and weakness based on the highest and lowest performing categories. The user is able to visualize what their leanness and category scores indicate using the graphical benchmarking scales that the tool displays. These scales show the user where they stand compared to other companies in the industry. Lastly, the tool displays the predicted categorization of the project's schedule and budget performance based on the embedded multiclass classification neural network.

This research establishes a comprehensive scoring system that assesses the leanness of construction projects. Moreover, it provides a detailed assessment of companies' implementation of lean principles through category scores that highlight areas of strength and weakness in the project. Additionally, it utilizes multiclass classification neural networks to predict and categorize project schedule and budget performance. Furthermore, it initiates a user friendly tool that provides a fully rounded assessment of construction projects based on lean principles. The benefit of developing such tool contributes not only to academic research but also to the professional field. This is due to the fact that the tool provides three main benefits. The first is that the user gets to know their overall lean score along with their weakest and strongest lean categories. This helps in strategically laying mitigation plans that will address performance flaws from their root cause. Moreover, in the case of strong categories, companies can further grow their employees' skills or develop a rewarding system to encourage greater performance. The second benefit is that companies can expect project performance through the predictions that the model makes. Hence, they are able to plan ahead and employ corrective actions in order to improve project performance. Lastly, the outcomes of the evaluation model are set to not only show the user their current status but also show them where the project stands as compared to the projects in the database using the leanness benchmarking scales. This helps to put the project in context compared to other projects and assists companies to benchmark themselves versus other companies.

7.2 Research Limitations and Recommendations for Future Research

The following are the limitations of the study along with their respective recommendations for future research:

1. The limitations of this research include having a limited database of only 30 projects. Accordingly, it is recommended for future research to conduct more project-based surveys in order to increase the database.

2. The limited number of projects in the database made it difficult for predictive data analysis tools to accurately predict project schedule and budget numerically. Consequently, the insufficient amount of data contributed to resorting to categorical classification. Hence, when the number of projects in the database increases, it is recommended to attempt numerically predicting schedule and budget performance.

3. The established neural network was built using the combination of all project types, ignoring the fact that schedule and budget performance varies according to the risks associated with each project type. Hence, it is recommended to establish separate neural networks based on the different project types as this will improve the accuracy of prediction.

4. Analysis of the strongest and weakest performing categories in the field can be done in order to further understand the challenges associated with implementing lean techniques in real life. This can provide another edge to the tool as it can suggest possible practical ways to strengthen areas of weakness and alleviate areas of strength.

5. Reiteration of expert-based surveys can be done periodically in order to update the relative importance of lean factors and accordingly update the scoring equation.

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Appendix A

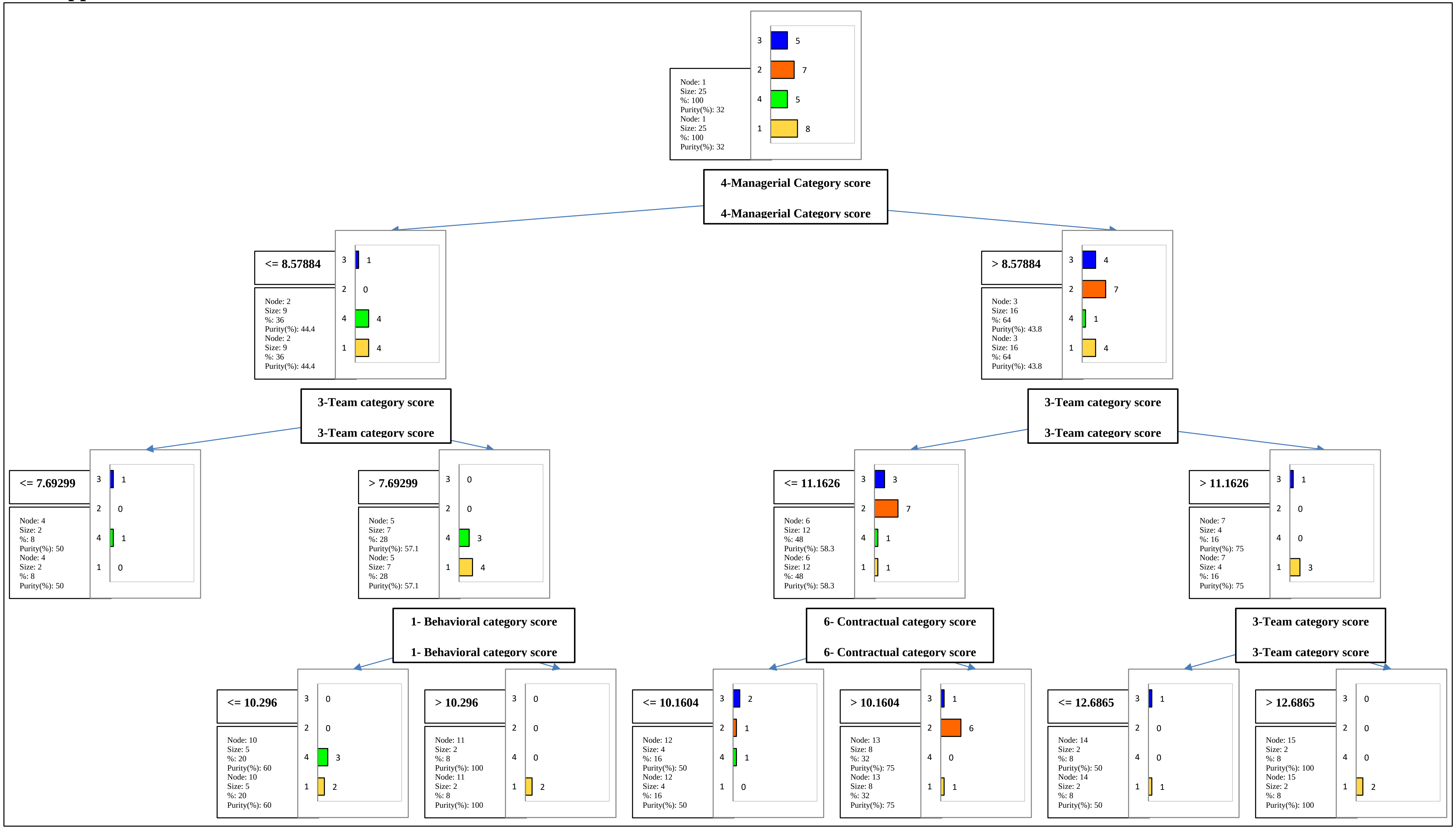

Figure 46: Decision tree predicting schedule performance

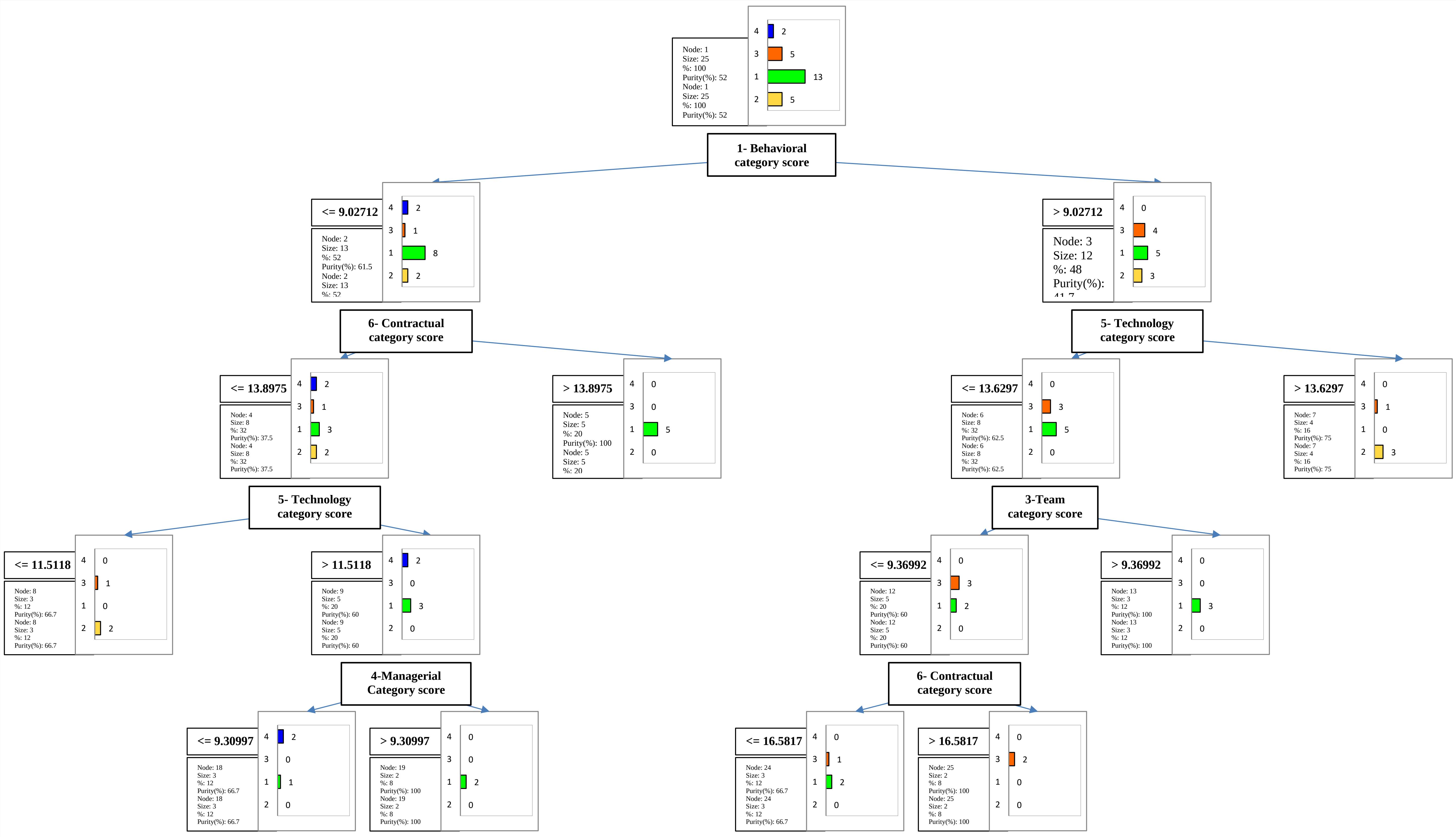

Figure 47: Decision tree predicting budget performance