Hybrid Neuro-Fuzzy Model for Construction Organizational Competencies and Performance

by

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Abstract

The construction industry is dynamic and complex that demands continuous quality, productivity, and performance improvement; making it challenging to achieve organizational success, superior performance, and competitive advantage. Organizational competencies have a significant influence on performance; hence, it is vital that construction organizations assess and enhance their competencies in order to improve performance. In addition, relating organizational competencies to performance is essential to identify target areas leading to improved performance. Furthermore, the variables that characterize organizational competencies and performance are both quantitative and qualitative in nature, and thus require measurement methods and modeling techniques such as artificial intelligence (AI) that can handle both variable types. However, stand-alone AI techniques have limitations for handling complex real-world problems. For instance, fuzzy systems are strong in reasoning and inference and explicit knowledge representation while weak in learning capabilities. On the other hand, artificial neural networks (ANNs) have powerful learning ability while poor in reasoning and inference. Thus, hybrid modeling approaches that combine two or more AI methods such as neuro-fuzzy systems (NFS), that combine the learning power of ANNs and functionality of fuzzy systems (i.e., improving reasoning and inference and explicit knowledge representation), are viable options used for modeling and solving practical real-world problems such as predicting performance.

NFS models have proven to be very effective for a wide range of real-world applications in construction owing to their robust, fast, and effective characteristics for solving complex problems. However, the application of different types of NFS models have some limitations such as (1) handling multiple outputs that are common in real-world construction processes and practices, and

(2) suffering from local minima and poor generalization that may lead to provide less accurate results and/or inadequate explanations for problems. Therefore, a hybrid NFS that combines evolutionary optimization technique i.e., genetic algorithm (GA) and multi-output adaptive neuro-fuzzy inference systems (MANFIS) is developed in this research to analyze multiple inputs and multi-outputs, that relate organizational competencies to performance, and predict multiple organizational performance metrics.

A systematic review and detailed content analysis of selected articles was conducted to identify, categorize, and rank organizational competencies affecting organizational performance. The categorization of competency and performance metrics, verified by the focus group, provides organizations with a systematic method to evaluate their competencies and improve their performance. The list of organizational competencies and performance metrics were piloted tested with a construction company prior to the data collection to ensure construct validity and the reliability of evaluation and measurement techniques used for data collection.

This research provides both researchers and construction industry practitioners a hybrid NFS modeling approach to analyze multiple organizational competencies as model inputs, relate them to performance, and predicting organizational performance. The hybrid NFS model enables to identify potential competencies for performance improvement, which provide organizations as well as construction practitioners with insight into targeted areas for future investment and expansion strategies in order to improve organizational performance, which further helps them to make the best decisions. Additionally, the hybrid NFS model has a great advantage since it can predict multiple organizational performance metrics simultaneously rather than developing independent models for each output.

Preface

This thesis is an original work by Getaneh Gezahegne Tiruneh. The research project, on which this dissertation is based on, received research ethics approval from the University of Alberta Research Ethics Board, Project Name "Fuzzy Hybrid Techniques for Competency Modeling for Construction Organizations and Projects", Study ID: Pro00068907, approved on November 04, 2016. This research was funded by the Natural Sciences and Engineering Research Council of Canada Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. Aminah Robinson Fayek.

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Dedication

To my beloved wife, Kokeb Tamirat Assefa.

Without your love, support, and patience, I would not be able to get to this stage.

To my son, Nolawi Getaneh Gezahegne.

I took your precious time to make this happen.

To my parents, Fantanesh Tibebu Mengesha and Gezahegne Tiruneh Belay.

You laid the foundation and discipline needed to complete this research work.

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List of Abbreviations and Notations

Abbreviations

ABC	Artificial bee colony
ACO	Ant colony optimization
AEC	Architecture, engineering, and construction
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANNs	Artificial neural networks
BIM	Building information modeling
CEM	Construction engineering and management
CI	Computational intelligence
CII	Construction Industry Institute
EAs	Evolutionary algorithms
FCM	Fuzzy *c*-means
FES	Fuzzy expert systems
FIS	Fuzzy inference system
FNN	Fuzzy neural network
FS	Feature selection
GA	Genetic algorithm

GA-ANFIS	Genetic algorithm-based adaptive neuro-fuzzy inference systems
GA-FS	Genetic algorithm-based feature selection
GA-MANFIS	Genetic algorithm-based multi-output adaptive neuro-fuzzy inference systems
GWO	Grey wolf optimization
ICA	Imperialist competitive algorithm
IPMA	International Project Management Association
KPIs	Key performance indicators
KPOs	Key performance outcomes
MIMO	Multi-input and multi-output
MISO	Multi-input and single-output
MF	Membership function
MLM	Middle and lower-level management
MLP	Multi-layer perception
NFS	Neuro-fuzzy systems
OPS	Office and project site staff
PerMs	Perception measures
PMI	Project management institute
PSO	Particle swarm optimization
RBF	Radial basis function

RII	Relative Importance Index
RMSE	Root mean square error
SEM	Structural equation model
SM	Senior management
SVM	Support vector machine

Notations

μ_X	Mean value of X
μ_Y	Mean value of Y
R_M	Weighted percentage of maturity
R_I	Weighted percentage of impact
R_{Im}	Weighted percentage of immaturity
R_D	Weighted percentage of disagreement
ρ	Pearson correlation coefficient
$\sigma_{X,Y}$	Covariance of the two variables (X, Y)
σ_X	Standard deviation of X
σ_Y	Standard deviation of Y
u_{ik}	Partition matrix
v_j	Cluster centers
x_N	Normalized values

Chapter 1 Introduction[1]

1.1 Background

The construction industry is dynamic, complex, and demands continuous quality, productivity, and performance improvement, due to the emergence of new procurement methods, contracts, and project delivery methods (Hanna et al. 2016; Kwak et al. 2015). The environment within which organizations in the construction industry operate is becoming more complex due to increasing uncertainties present in technology, budgets, and development processes, making it challenging to achieve organizational success and competitive advantage (Acur et al. 2010; Radujković et al. 2010). Several studies (e.g., Beatham et al. 2004; Hanna et al. 2016; Radujković et al. 2010) have criticized the construction industry for its underperformance. For instance, Radujković et al. (2010) argue that the construction industry still suffers from inefficiency and ineffectiveness and lags far behind all other industries in terms of performance. Hanna et al. (2016) concur that the construction industry continues to suffer from declining productivity at a rate of -0.5% per year since 1960, compared to other industries that are growing at a rate of 1.7% annually. Some of the challenges that have long been recognized as inhibiting the performance of the construction industry include

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problems in its structure (e.g., fragmentation), the dynamic nature of the industry and business environment, the changing nature of the work, and the increasing competition (Beatham et al. 2004; Kwak et al. 2015). Researchers therefore emphasize the importance of adopting effective strategies and performance measurement methods that will improve the performance of organizations in the construction industry (Acur et al. 2010; Horta and Camanho 2014). Loufrani-Fedida and Missonier (2015) argue that recent developments in theory and practice have placed competencies at the center of an organization's success, resulting in a focus on defining critical competencies that must be implemented in the organization's context to ensure better performance. Therefore, in order to achieve better performance and competitiveness, construction organizations (i.e., owners, consultants, and contractors) need to explore new approaches for assessing and enhancing their competencies (Giel and Issa 2016; Omar and Fayek 2016; Sparrow 1995).

Previous competency studies emphasize only select aspects, such as individual/personal or managerial competencies (Salajeghe et al. 2014). Some studies have been conducted at the project level (Hanna et al. 2016, 2018; IPMA 2006, 2015; Omar and Fayek 2016; Salajeghe 2014). However, competency studies at the organizational level are few (Edgar and Lockwood 2008; Escrig-Tena and Bou-Llusar 2005; Sparrow 1995). Competency studies at an organizational level need to account for the unique nature of construction, which is widely regarded as complex, full of uncertainties, and contingent on changing environments. As such, there remains a need for a comprehensive analysis of all aspects of organizational competencies that improve performance for construction organizations operating in a highly competitive global market.

1.2 Problem Statement

The existing body of knowledge provides a solid foundation for competencies identification in the literature, there are still some gaps in competency and performance research in construction. For instance, evaluating organizational competencies has received significant attention by past researchers, based on its importance in organizational effectiveness, competitiveness, and performance, although most of the research is in domains other than construction (Acur et al. 2010; Lokshin et al. 2009). Studies in developing a comprehensive framework for evaluating and measuring organizational competencies; assessing its impact on organizational performance; and identifying competency and performance relationship at an organization level is few. Thus, further investigation is required to categorize and measure competencies necessary for organizations in different construction industry sectors to perform well. The current gaps that will be addressed in this research are summarized in this section.

To outperform the competition in the long run and achieve sustained competitive advantage in the market, it is critical for organizations in the construction industry to identify and define their competencies (Giel and Issa 2016; Medina and Medina 2014; Omar and Fayek 2016). Published literature is one of the main sources of information for identifying organizational competencies influencing organizational performance. Although organizational competency is a major research focus in many disciplines such as business, human resources, and management, limited research has been conducted in the construction domain (Tiruneh and Fayek 2020). Moreover, there has been no systematic literature review and detailed content analysis done on articles that deal with identification and categorization of organizational-level competencies and performance measures in construction. Thus, the ***first gap*** that will be addressed in this thesis is the lack of systematic review and content analysis of published articles related to organizational competencies and performance measures in construction.

Real-world construction problems are characterized by their non-specificity, uncertainty, complexity, dynamism, and non-linearity, which challenges construction management and makes accurate predictions difficult (Elbaz et al. 2020). It is also difficult to explicitly represent such complex construction engineering and management (CEM) problems in a deterministic mathematical or statistical model due to lack of sufficient data (i.e., limitations in quantity and quality of data), and subjective uncertainty associated with the problem. Therefore, artificial intelligence (AI) based models such as hybrid neuro-fuzzy systems (NFS) are suitable to solve complex problems with nonlinear relationship and subjective uncertainty that offer high accuracy and low cost is one feasible approach to predict performance (Cheng et al. 2015; Tiruneh et al. 2020). However, a review of past studies showed that NFS are limited to select aspects of construction applications such as cost, risk, human resource, quality, and performance management. Major challenges of these studies are to find synthesized information in the existing literature and useful recommendations to researchers regarding the suitability of NFS techniques to any specific application of the construction domain. To date, there has been no systematic literature review and detailed content analysis done on NFS in construction applications. Moreover, suitability of a particular NFS to problems within construction application, detailed and integrated categorization of the various NFS, and identification of criteria that enables categorization of NFS and recommend a suitable subset of NFS approaches for construction applications has not been done. Thus, the ***second gap*** that will be addressed in this thesis is the lack of systematic review and content analysis of published articles related to NFS modeling techniques in construction.

The variables that capture construction organizational competencies and performance are highly dimensional as well as both quantitative and qualitative in nature. Organizational competency and performance modeling techniques that can handle both quantitative and qualitative variable types, uncertainty, complex, and nonlinear relationships is also very important. Implementing dimensionality reduction techniques such as feature selection (FS) is critical to develop a concise and interpretable model with low model complexity and improved accuracy. Therefore, an FS approach that is suitable for high dimensionality of features and limited data instances is critical for obtaining features that represent the original feature subset well. FS using population-based or evolutionary algorithms (EAs) such as a genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC), and ant colony optimization (ACO) are employed, which can yield optimum results and are computationally feasible (Tiruneh and Fayek 2019). In this research, GA optimization is used for FS to reduce the dimensionality of input features (i.e., organizational competencies) to select a reduced number of features that represent the original feature subset for modeling. Thus, the ***third gap*** that will be addressed in this thesis is the lack of systematic GA-based FS methodology for data attributes with high dimensionality and limited data instances common in construction problems.

Modeling techniques that relate construction organizational competency to performance is essential for identifying target areas to improve organizational performance. However, most proposed methods in literature are conceptual models while the remaining are regression models to relate competency and performance. Therefore, AI techniques are suitable to solve such complex real-world problems for an uncertain environment (Elmousalami 2020). However, Existing literature indicates that stand-alone AI techniques have limitations for handling real-world problems mainly because of the complexity of real-world problems and uncertain/unclear or lack of enough information (Aydin and Kisi 2015; Chan et al. 2009; Tokede et al. 2014). Hybrid NFS modeling approach that combine the strength of artificial neural networks (ANNs) and fuzzy systems are viable options used for modeling and solving practical real-world problems such as predicting performance. For instance, fuzzy systems are strong in reasoning and inference and explicit knowledge representation while weak in learning capabilities (Aydin and Kisi 2015; Chan et al. 2009). On the other hand, ANNs have powerful learning ability while poor in reasoning and inference (Cheng and Ko 2003; Tokede et al. 2014; Jin 2010). Thus, a NFS model that combine the learning power of ANNs and functionality of fuzzy systems (i.e., improving reasoning and inference and explicit knowledge representation) is developed in this research to analyze organizational competencies and predict multiple performance metrics. Despite their broad applicability to several fields of engineering, conventional NFSs have a multi-inputs single-output (MISO) structure, as in adaptive neuro-fuzzy inference system (ANFIS), so they fail to directly deal with multi-input multi-output (MIMO) systems (Acampora et al. 2014; Cheng et al. 2002). As a result, various approaches have used improved ANFIS that can handle MIMO systems, such as MANFIS (Acampora et al. 2014; Benmiloud 2010; Cheng et al. 2002). Although the use of NFS that can handle MIMO problems is widely used in research disciplines other than construction, few research has been conducted in the construction domain which is characterized by complex and nonlinear multiple input-output relationship of real-world problems. To date, a great gap has existed in addressing MIMO NFS modeling techniques for construction problems, specifically for predicting multiple performance metrics.

NFS models such as ANFIS have good performance with desirable accuracy compared to the conventional mathematical or regression models in real engineering practice (Yuan et al. 2014). However, an argument exists as to whether ANFIS can yield reasonable solutions with robustness because AI models still suffer from local minima and poor generalization (Elbaz et al. 2020; Yuan et al. 2014). As a result, it may provide less accurate results and/or distorted or inadequate explanations for problems (Elbaz et al. 2019). To overcome these limitations, ANFIS needs to be optimized with EA techniques, such as GA, PSO, ABC, ACO etc. (Elbaz et al. 2019, 2020). MANFIS has similar limitations that ANFIS has (i.e., slow computational convergence and potential of being trapped in local minima), which results in low accuracy and poor generalization. Using a hybrid of MANFIS and EAs techniques, such as GA is vital to improving MANFIS performance. As a result, a hybrid model of GA and MANFIS i.e., GA-MANFIS is developed in this research. Thus, the ***fourth gap*** that will be addressed in this thesis is the lack of a hybrid NFS model capable of capturing the complex non-linear relationships between organizational competencies and performance that can handle MIMO problems. Moreover, enhancing model prediction performance by hybridizing MANFIS with GA will be addressed in this thesis for predicting multiple organizational performance metrics using organizational competencies.

1.3 Research Objectives

The hypothesis of this research is as follows:

> "*Construction organizational competencies that influence organizational performance can effectively be modeled and analysed using a hybrid NFS with EAs such as GA to predict multiple organizational performance metrics by analyzing multiple organizational competencies*."

The main objective of this research is to develop a hybrid NFS model that can handle MIMO problems to evaluate and analyze organizational competencies, relate competencies to performance, and predict multiple organizational performance metrics simultaneously. The detailed objectives of this research are grouped under the following six main categories:

1. To address the lack of systematic review and content analysis of published articles related to organizational competencies and performance in construction; perform a critical examination of commonly used organizational competencies and performance metrics in construction; and identify, systematically categorize, and rank organizational competencies influencing organizational performance.

2. To provide a systematic literature review and content analysis on NFS techniques in construction applications, classify NFS in CEM research, identify criteria to evaluate appropriateness and suitability of NFS in CEM applications, and recommendations to researchers regarding suitable subsets of NFS techniques for solving different types of CEM problems.

3. To provide a systematic GA-based FS approach for dimensionality reduction of data attributes to develop a concise model that helps reduce computational time and improve model accuracy.

4. To develop a hybrid NFS model to (a) handle MIMO problems inherent in construction processes and practices; and (b) relate organizational competencies to performance and predict multiple organizational performance metrics by analyzing organizational competencies.

5. To advance the state of the art in NFS modeling for organizational competencies and performance by providing a membership function (MF) optimization to improve the hybrid NFS model prediction performance using EAs techniques (i.e., GA).

6. To provide construction industry practitioners with (a) a competency and performance modeling and analysis approach that will help industry practitioners to understand the effect of organizational competencies on organizational performance; (b) an approach that will assist construction industry practitioners to model and analyze the impact of organizational competencies on performance; and (c) an approach to identify potential competencies for performance improvement, which provide organizations as well as construction practitioners with insight into targeted areas for future investment and improvement strategies in order to increase organizational performance.

1.4 Expected Contributions

The expected contributions of this research are categorized as academic and industrial contributions, based on their relevance to academic researchers and construction industry practitioners, respectively.

1.4.1 Academic Contributions

The expected academic contributions of this research are as follows:

1. Providing a systematic and in-depth content analysis of published articles related to organizational competencies and performance metrics in construction, and a useful reference on a comprehensive hierarchical list of competencies and performance metrics for future analysis and modeling purposes.

2. Providing a systematic literature review and content analysis of NFS techniques in different construction applications and recommendations to researchers regarding suitable subsets of NFS techniques for solving different types of CEM problems.

3. Providing an approach, using hybrid NFS modeling, that can handle multiple outputs in

analyzing multiple organizational competencies as model inputs and predicting multiple organizational performance metrics simultaneously with a good accuracy.

4. Contributing to the advancement of the state of the art in NFS modeling for organizational competencies and performance in construction by:
    a) providing a method for handling MIMO problems;
    b) providing a structured and systematic GA-FS approach to reduce the dimensionality of data to develop a concise model with a better accuracy; and
    c) implementing MF/parameter and model optimization to improve model performance.

1.4.2 Industrial Contributions

The expected industrial contributions of this research are as follows:

1. Providing a useful reference of a comprehensive hierarchical competency and performance metrics for organizations in construction for future competency and performance identification, analysis, and modeling purposes.

2. Provide an analysis approach to identify organizational competencies that have a significant impact on organizational performance and determine competencies that need improvement that help to increase performance.

3. Providing a modeling and analysis approach that allows construction industry practitioners to assess organizational competencies and predict organizational performance.

4. Providing a hybrid NFS modeling approach to understand the impact of organizational competencies on performance and predict multiple organizational performance metrics.

1.5 Research Methodology

Figure 1.1 depicts a four-stage process adopted in this research to achieve the objectives listed in Section 1.3. A description of these stages are provided in this section.

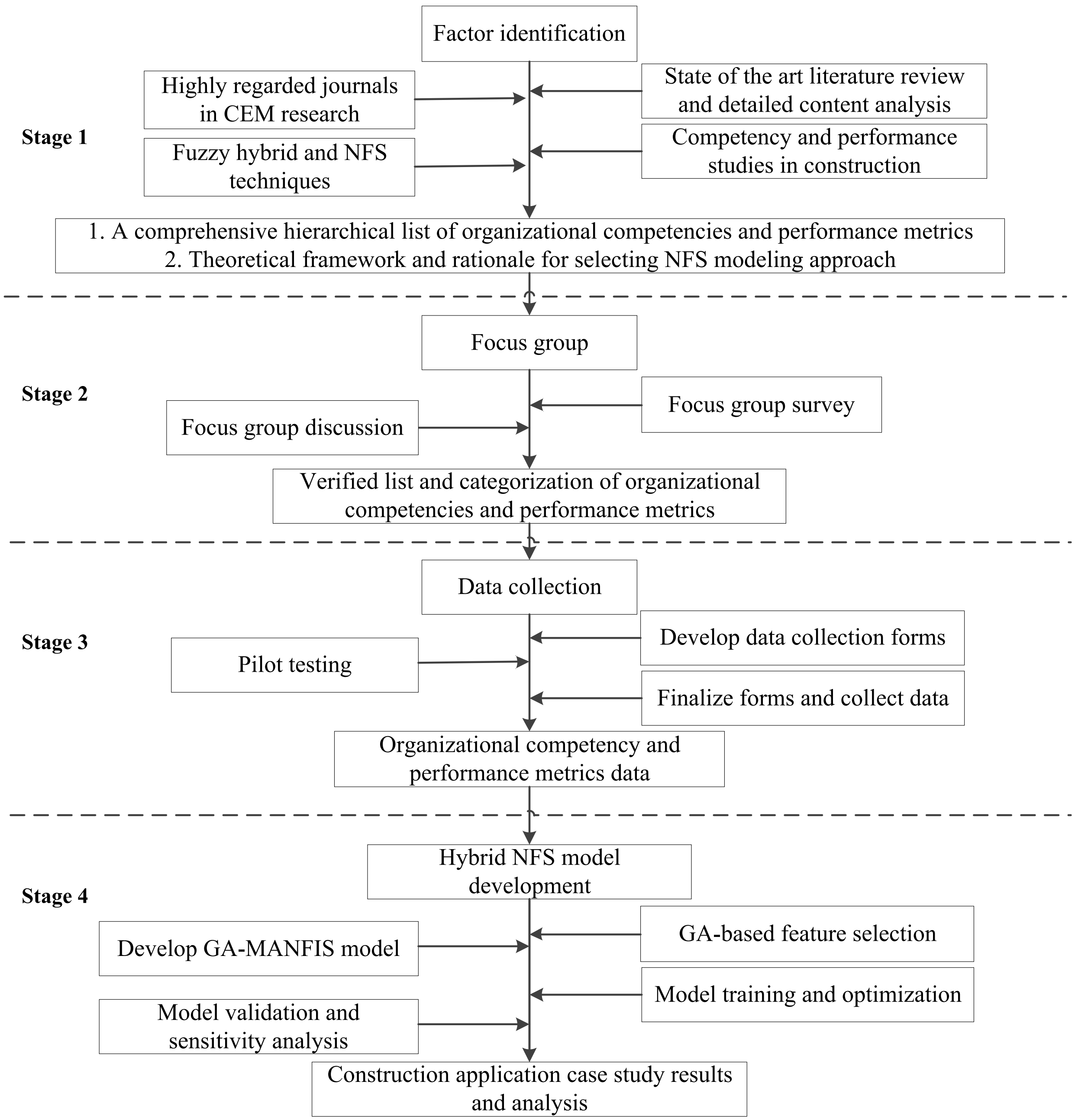

Figure 1.1. Research methodology stages

1.5.1 The First Stage

In the first stage of this research, the research commenced by conducting comprehensive state of the art review on competency and performance in general, with a specific focus on organizational competency and performance in construction. A systematic review and detailed content analysis was conducted. Organizational competencies and performance commonly used in the construction were investigated. A comprehensive list of organizational competencies and performance metrics were identified from the selected articles; categorized systematically based on the nature of the competencies; and ranked based on their frequencies, i.e., the total number of references (hits) each competency had.

Past studies focusing on hybrid fuzzy techniques and NFS for organizational competencies and performance were closely examined to identify the research gaps outlined in Section 1.2. After conducting the literature review, the main theoretical framework of the research and rationale for selecting the NFS modeling approach for organizational competencies and performance were established. A systematic review and detailed content analysis related to NFS in construction was also conducted. Common NFS methods used in the construction domain were investigated. Also, commonly used NFS modeling approaches in construction were identified and suitability of NFS in CEM applications was investigated.

1.5.2 The Second Stage

In the second stage of this research, a focus group was conducted to verify and validate the list and categorization of identified organizational competencies influencing organizational performance as well as performance metrics and their hierarchically structured categorization. The experts participated in the focus group reviewed the list and proposed additional competency and performance metrics they thought important at an organization level. The initial list of organizational competencies was then updated to incorporate feedbacks from the focus group and include proposed additional competencies which are backed by literature. The focus group allowed for the development of a comprehensive list of organizational competencies and performance metrics that not only considers the literature in construction and non-construction domains but also captures the opinions of construction experts practicing in the construction industry.

1.5.3 The Third Stage

In the third stage of this research, data collection forms were prepared, and pilot tested prior to the data collection. Data collection forms were developed based on the finalized list of organizational competencies and performance metrics based on the focus group results. Furthermore, the list of organizational competencies and performance metrics were pilot tested with a construction company prior to the data collection to ensure that respondents understood the data collection forms as well as to check applicability of the evaluation, assessment, and measurement scales and techniques of the data collection forms in CEM organizations. Then, data collection was performed in a construction company actively involved in industrial projects. Data collection for organizational competencies was conducted via an online survey through Survey Monkey. Actual company performance metrics data were collected and extracted from relevant actual organizational/project documents at the organizational level (operational) and project level.

1.5.4 The Fourth Stage

In the fourth stage of this research, the hybrid NFS model was developed in two phases: (i) performing GA-FS to reduce the dimensionality of data and (ii) development of a hybrid GA-MANFIS model that can handle MIMO real-world engineering problems to predict multiple organizational performance metrics. Performing the GA-based FS encompasses FCM parameter optimization and GA-FS to reduce the dimensionality of original raw data to build a concise and efficient predictive model. Therefore, a GA-based FS is conducted to reduce the dimensionality of data attributes and help reduce computational time and improve model accuracy. The hybrid GA-MANFIS model is developed using input features (i.e., competencies) identified as a result of the GA-FS. The GA- MANFIS is designed by decomposing it into seven MISO adaptive neuro-fuzzy systems that corresponds and predicts a single output. The training and optimization of the MANFIS model is conducted using GA optimization. Finally, the hybrid GA-MANFIS models were validated by evaluating the performance of the GA-MANFIS model by comparing model outputs (i.e., predicted results) against the testing dataset using the fitness function (i.e., root mean square error, RMSE). Sensitivity analysis is also conducted to identify the main parameters of the GA-MANFIS model that affect the model outputs significantly.

1.6 Thesis Organization

Chapter 1 presents a brief background of the research, the problem statement, and objectives of this research. The expected academic and industrial contributions, and the research methodology are also provided in this chapter. The rest of this thesis is organized as follows.

Chapter 2 presents an overview of organizational competencies and performance metrics commonly used in construction domain. In addition, state of the art review on NFS modeling techniques in construction is presented.

Chapter 3 presents a content analysis and focus group study to verify and validate the proposed comprehensive list of systematically categorized and ranked organizational competencies affecting organizational performance commonly used in construction. The proposed classification method and the identified organizational competencies and performance metrics were used as input to develop the data collection forms.

Chapter 4 presents a comparative analysis of organizational competencies influencing organizational performance based on perspectives of survey respondent groups. Furthermore, Pearson correlation analysis was performed to investigate relationship between organizational competency and organizational performance.

Chapter 5 presents the overall methodology and the detailed steps for developing the hybrid NFS model that can handle multiple outputs. Finally, model verification and validation methods applied are also described.

Chapter 6 presents a case study to illustrate the proposed NFS modeling methodology for analyzing organizational competencies and predicting multiple organizational performance metrics. The verification and validation for the NFS models are also presented in this chapter.

Chapter 7 presents the conclusions, contributions, and limitations of this research along with recommendations for future research.

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Chapter 2 Literature Review[2]

2.1 Introduction

This chapter aims to provide the background related to this research by conducting state of the art review on organizational competencies and performance as well as NFS modeling techniques, with a specific focus on organizational competencies influencing performance. Also, this chapter presents the main theoretical framework of the research and the rationale for selecting the proposed modeling method for organizational competencies and performance. In the following sections, a brief background on organizational competencies and performance and their categorization is provided. A background on the relationship between competency and performance is presented which establishes the theoretical framework and rationale of this research. An overview of competency and performance modeling methods are presented; and their limitations established. The different NFS modeling techniques and their applications in construction is also discussed. Moreover, the limitations of conventional NFS models for construction applications as well as for

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analyzing competency and predicting performance are highlighted. Finally, a summary of this chapter is provided.

2.2 Organizational Competencies and Performance

2.2.1 Organizational Competency

The concept of "competency" was first proposed in McClelland's (1973) seminal paper, which argues that traditional intelligence tests do not predict future life success. Boyatzis (1982) coined the definition of competency as "an underlying characteristic of a person, which results in effective and/or superior performance in a job." Succar et al. (2013) view competency in terms capability (i.e., the ability to perform a task) and/or maturity (i.e., the degree of excellence in performing a task). The term competency reflects a generic set of abilities suitable for implementing a task and assessing the capability and/or maturity to perform a task (Succar et al. 2013). Competency is a combination of knowledge, skills, and abilities as well as experience to accomplish a specific task (IPMA 2015; Succar et al. 2013). Having a skill presupposes some relevant knowledge, while having ability presupposes relevant skills and knowledge for implementing a specific task, in the right manner, and at the right time. Furthermore, experience plays a significance role in competency. Without experience, competency can neither be demonstrated nor improved. To successfully perform assigned roles, individuals need to accumulate enough experience to complement their competencies (IPMA 2015). In general, competencies are defined as combinations of (1) motives, (2) traits, (3) self-concepts, (4) attitudes or values, (5) content knowledge or cognitive behavioral skills, and (6) any individual characteristic that can be reliably measured or counted and that can be shown to differentiate superior from average performers (Hanna et al. 2018).

The literature indicates a widespread misconception of organizational competencies, which are often perceived narrowly as individual employee skills and capabilities, rather than overall cross-company core competencies that drive integrated business execution (Edgar and Lockwood 2008). Past studies (e.g., Loufrani-Fedida and Missonier 2015; Loufrani-Fedida and Saglietto 2016; Succar et al. 2013) attempt to capture organizational competency using a multi-level approach at an individual, team/collective, and organizational level as shown in Figure 2.1. For instance, enhancing individual competencies showed an increase in individual performance (Ahadzie et al. 2009, 2014; Levenson et al. 2006). Project team/crew task completion competency showed improvement of task performance (Liu et al. 2010). An increase in project performance in terms of cost and schedule metrics was achieved by improving project competencies (Omar and Fayek 2016). Studies also showed development of competencies, a particular set of skills, and capabilities helped to achieve superior performance (Bolivar-Ramos et al. 2012; Liang et al. 2013; Subramanian et al. 2009).

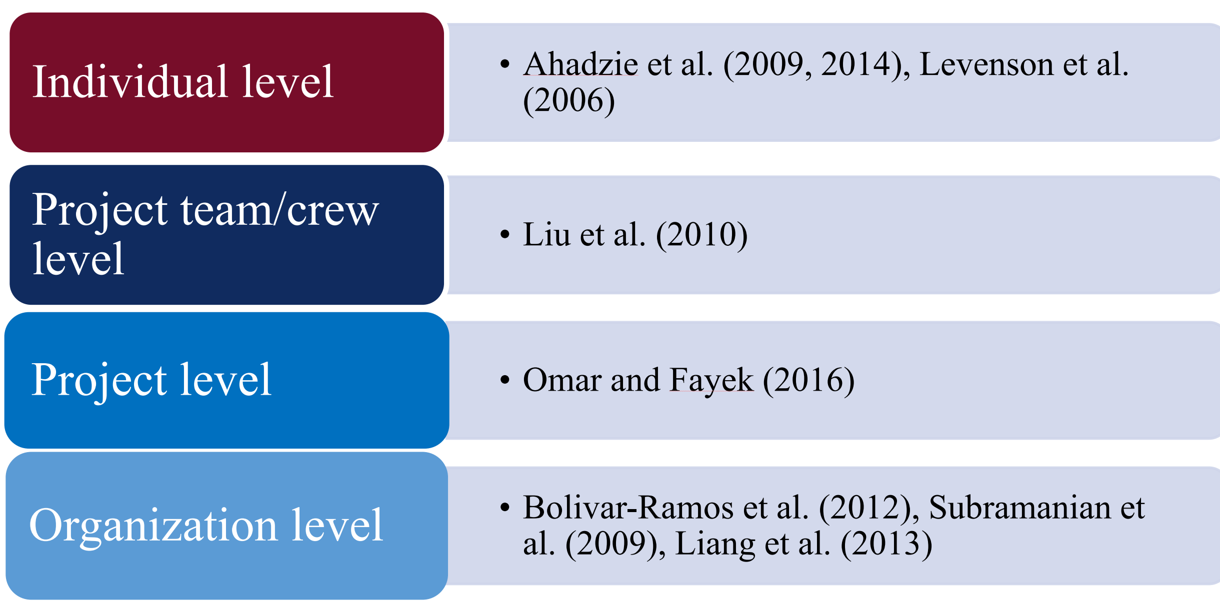

Figure 2.1. Multilevel view of organizational competency

Some studies differentiate between capabilities and competencies (Succar et al. 2013; Walsh and Linton 2001). For instance, Succar et al. (2013) view organizational competency as multi-level, consisting of competency (i.e., an individual's ability) and capability (i.e., a team or organization's ability) to perform a specific task, as well as maturity (i.e., a team or organization's excellence) in performing a task. Their study argues that organizational competency is an aggregation of individual and/or team/group competencies. According to Crawford (2015), the concept of maturity is used to describe the state of an organization's effectiveness at performing certain tasks. The competency versus maturity approach perceives organizational competency (i.e., capability and/or maturity) as an aggregation of individual and/or team capability/maturity. This approach enables performance assessment and improvement that teams and/or organizations aspire to achieve (Succar et al. 2013; Walsh and Linton 2001). However, the competency versus maturity approach fails to capture the overall aspect of an organization that goes beyond simply aggregating individual competency and/or team capability or maturity. Escrig-Tena and Bou-Llusar (2005) assert that the concept of competencies consists of individual/personal competency (e.g., experience, technical knowledge, skills, and abilities) and corporate competencies (i.e., a combination of skills and knowledge that belong to the organization itself. They argue that organizational competencies are a combination of skills and knowledge, not only possessed by individual members, but also embedded in company processes and systems; thus, these skills and knowledge remain in the organization even when individuals leave the company. Accordingly, Loufrani-Fedida and Missonier (2015) view competency in a broad sense as "the ability of an individual, a team, or a company to mobilize and combine resources in order to implement an activity." Acur et al. (2010) consider the development of organizational competencies as antecedents of performance. For example, Sparrow (1995) stresses that innovative technologies, resources, and capabilities of the organization that are connected to overall performance are necessary to sustain a high level of competitiveness. Rosas et al. (2011) maintain that organizational competency is the ability of an organization to perform activities, tasks, or processes aimed at achieving a specified number of outcomes (i.e., performance). Accordingly, many companies define required competencies based on the goals that are identified within the context of their strategic plan. Thus, organizational competencies are a set of processes and practices that form the organization's main system for storing knowledge and that determine the regular operation of organizational functions (Escrig-Tena and Bou-Llusar 2005). For this research, Tiruneh and Fayek's (2018) working definition of organizational competency as "an integrated combination of resources, particular sets of skills, necessary information, technologies, and the right corporate culture that enable an organization to achieve its corporate goals, competitive advantage, and superior performance" will be used.

2.2.2 Organizational Performance

Performance is of particular interest to the construction industry, where organizations focus on improving their performance (Rathore and Elwakil 2015). Predicting construction organizational performance helps identify weak organizational processes and practices, which can then be enhanced, improving efficiency and profitability (Rathore and Elwakil 2015). However, Poveda and Fayek (2009) argue that performance is such a complex process that no single factor can be used to predict or evaluate it. It is a major challenge to predict performance in measurable terms such that it can be used for budgeting and control activities (Georgy et al. 2005; Lin and Shen 2007). Yun et al. (2016) stresses the need for effective and flexible performance measurement methods for organizations so they can be successful in a dynamic business environment such as the construction industry. An organization's performance depends greatly on its people and their competencies (Chung and Wu 2011). Practitioners in construction companies always strive to measure performance, compare planned performance to actual performance, and take corrective action in order to improve performance (Georgy et al. 2005; Lin and Shen 2007). Therefore, research in the construction domain has largely been focused on establishing performance measurement frameworks for construction companies (Deng and Smyth 2014; Horta and Camanho 2014).

2.2.3 Categorization Methods for Organizational Competencies and Performance Metrics

2.2.3.1 Categorization of Organizational Competencies

A wide range of competency models and frameworks were reviewed in order to identify and categorize organizational competencies. Some of the reviewed studies include the International Project Management Association (IPMA) individual competence baseline (ICB) models (i.e., IPMA Competence Baseline, Version 3.0 (IPMA 2006) and Individual Competence Baseline Version 4.0 (IPMA 2015)), and the fuzzy hybrid model (Omar and Fayek 2016), competency frameworks (Janjua 2012; Salajeghe et al. 2014). These competency models and frameworks are reviewed and summarized below.

Past competency models categorize competencies in various ways. For instance, IPMA (2006) identified 46 project management competencies and classified them into three major categories: technical, behavioral, and contextual. Omar and Fayek (2016) categorized 41 construction project competencies into two groups as functional and behavioral. IPMA (2015) developed 28 competencies categorized as practice, people, and perspective competencies, which are analogous to the technical, behavioral, and contextual competencies of IPMA (2006). Janjua et al. (2012)

derived five competency classes: functional, generic management, social skills, cognitive skills, and personal characteristics. Salajeghe et al. (2014) developed a framework for competency assessment with five categories of competencies: knowledge, performance, personal, industry, and organizational competencies. Takey and Carvalho (2015) classified project management competencies into the four categories of project management processes, personal, technical, and context and business. Loufrani-Fedida and Missonier (2015) grouped competencies into three categories: functional, integrative, and collective. The variety of and approaches to competency categorization indicate that organizations define their competencies and categorize them on the basis of their needs and strategic goals. Escrig-Tena and Bou-Llusar (2005) developed a model to evaluate organizational competency, which grouped nine competencies into four categories: managerial, input-based, transformation-based, and output-based. Walsh and Linton (2001) differentiated between competencies and capabilities: competencies refer to firm-specific technologies and production-related skills (i.e., technical competencies), while capabilities refer to firm-specific business practices, processes, and culture (i.e., managerial capabilities). Walsh and Linton (2001) proposed an organizational competencies pyramid that defines organizational competencies as an aggregation of both technical competencies and managerial capabilities. Giel and Issa (2016) developed a framework for evaluating building information modeling (BIM) competencies in three categories: strategic, administrative, and operational. Their framework provides an assessment of BIM maturity for owner organizations to evaluate their technical knowledge, improve their BIM requirements during design and construction, and improve the efficiency of their postconstruction operations (Giel and Issa 2016). Loufrani-Fedida and Saglietto (2016) proposed an integrative approach to map multi-level competencies to the knowledge management, human resource management, and strategy of the organization. However, their study does not link these competencies to organizational performance and lacks external validity to apply it broadly. The framework proposed by Salajeghe et al. (2014) may be applicable at an organizational level, given the multi-level approach of the categories developed, although it was developed for measuring project manager effectiveness (i.e., an individual level). The model developed by Omar and Fayek (2016) can be extended to the organizational level, since it captures behavioral and functional competencies at the project level and links those competencies to project performance.

Relating organizational competency to performance is essential for identifying target areas where performance can be improved. Previous studies do not capture overall organizational competency and performance and the dynamic and complex nature of organizations. Such studies consider either individual (IPMA 2015; Janjua et al. 2012; Salajeghe et al. 2014; Takey and Carvalho 2015) and/or project-level competencies (IPMA 2006; Loufrani-Fedida and Missonier 2015; Omar and Fayek 2016), but fail to frame them at the organizational level. Other studies that model organizational competencies focus only on one specific aspect of the organization, such as quality management competency (Escrig-Tena and Bou-Llusar 2005; Walsh and Linton 2001), BIM competency (Giel and Issa 2016; Succar et al. 2013), and software project management (Loufrani-Fedida and Saglietto 2016). To address these gaps, a more comprehensive categorization of organizational competencies is developed in this research that can be applied at different levels within an organization; it also proposes a model to relate competencies to organizational performance measures. The proposed categorization of organizational competency and performance measures, identified through a thorough literature review and detailed content analysis, will help to capture organizational processes and practices as a whole for companies involved in the construction industry.

2.2.3.2 Categorization of Organizational Performance

The highly competitive environment of the construction industry creates pressure on organizations to implement systematic performance measurement methods so they can continuously improve their performance (Horta and Camanho 2014). The use of key performance indicators (KPIs) dominates the practice of performance measurement in construction (Deng and Smyth 2014). Many performance measurement frameworks exist for organizations in the construction industry, such as those developed by Beatham et al. (2004), Horta and Camanho (2014), Radujković et al. (2010), and Yun et al. (2016). However, the literature indicates that along with KPIs, key performance outcomes (KPOs) and perception measures (PerMs) can also be used effectively in the construction industry to measure performance (Beatham et al. 2004; Radujković et al. 2010). KPIs are leading indicators that can predict future trends in organizational operations, thus helping to identify problems at early stages and providing opportunities for change. In contrast, KPOs are results of completed tasks, activities, or processes; hence, KPOs are lagging indicators and do not provide opportunities for change. PerMs can be either leading or lagging, depending on the time at which they are measured. PerMs are subjective in nature and are often measured through surveys and interviews (Radujković et al. 2010).

2.2.4 Relationship Between Organizational Competency and Performance

A review of past studies revealed a significant positive relationship between competencies and organizational performance (Bolivar-Ramos et al. 2012; Liang et al. 2013). For instance, Levenson et al. (2006) revealed a positive relationship between higher managerial competency levels and individual-level performance. On the other hand, Rambe and Makhalemele (2015) argued the relationship between managerial competencies and firm performance is not necessarily direct but is rather mediated by some intervening organizational and environmental variables. Levenson et al. (2006) also found a positive relationship between mentoring on the competency system and individual performance, suggesting a route through which organizations can use competency systems to improve performance. Managerial competence is considered a key factor contributing to the performance and survival of any organization (Rambe and Makhalemele 2015). Bolivar-Ramos et al. (2012) verified fostering of competencies (i.e., technological distinctive competencies, organizational learning, and organizational innovation) and strategic capabilities have positive effects on improving organizational performance. If the organization is able to successfully generate market intelligence, disseminate it across departments and then respond to it, it should result in the development of a particular set of skills and resources (or organizational competencies) that will produce the outcome of superior performance (Subramanian et al. 2009).

2.3 Overview of Organizational Competency and Performance Modeling Methods

Competency models are a realization of a specific combination of knowledge, skills, and other personal characteristics necessary for efficient execution of tasks (i.e., that are needed for effective performance) in the organization (Campion et al. 2011; Krajcovicova et al. 2012). Competency models can be developed for specific jobs, job groups, organizations, occupations, or industries (Campion et al. 2011; Krajcovicova et al. 2012; Salajeghe et al. 2014). Krajcovicova et al. (2012) stresses that the development of competency model depends primarily on the intentions and direction of the company. According to Salajeghe et al. (2014) competency models can help industries align their initiatives to their overall business strategy. Past competency and performance modeling methods available in literature can be categorized into six groups: conceptual, correlation/regression, ANN, fuzzy expert systems (FES), and hybrid fuzzy methods (Tiruneh and Fayek 2018). Each of these modeling methods are discussed below.

Competency-based multidimensional conceptual models have been proposed to determine the performance of project managers. For instance, project manager competency development model (PMCDF) model (PMI 2007), international competence baseline (ICB) model (IPMA 2006, 2015), and competency assessment model (Salajeghe et al. 2014) are some of the conceptual models. Moreover, conceptual models that links competencies to performance showed the positive impact of competencies on performance (Ahadzie et al. 2009, 2014; Boucher et al. 2007; Suhairom et al. 2014). However, the conceptual models are generic and limited to specific aspects; hence do not capture industry and organizational contexts.

Statistical and structural equation model (SEM), correlation, and/or regression models have been used to analyze competencies and determine performance. Dainty et al. (2004, 2005) developed a statistical model to determine competencies defining superior management performance. Cheng et al. (2007) developed an empirical model using path analysis to examine the effects of competencies and job performance on overall project performance. Bolivar-Ramos et al. (2012) developed an SEM model to determine organizational performance. Altuncan and Tanyer (2018) proposed a performance assessment methodology for conflict management based on competency theory. However, these statistical and SEM models do not capture overall organizational competency and performance as well as the dynamic and complex nature of organizations.

Some studies employed regression models that correlate project managers' behavior with the final project outcomes (Ling 2002, 2004; Cheng 2007). A regression model developed by past studies confirmed the impact of organizational competency on organizational performance (Liang et al. 2013; Levenson et al 2006; Liu et al. 2010; Subramanian et al. 2009). Liang et al. (2013) indicated that the variables of core competences are positively correlated with organizational performance.

However, the regression models discussed do not capture complex relationships and subjective uncertainty.

Few studies used ANN and FES to determine and predict performance (Elwakil et al. 2009; Poveda and Fayek 2009). However, ANN models lack inference and explicit knowledge representation while FES lacks learning capability. Fuzzy hybrid models that combine ANN and fuzzy systems have also been developed to remedy the drawbacks of fuzzy systems and ANN models (Georgy et al. 2005; Omar and Fayek 2016).

Modeling techniques that relate construction organizational competency to performance that enable to determine and predict performance are essential for organizations in the construction industry (Tiruneh and Fayek 2020). Moreover, predicting organizational performance helps to identify weak organizational processes and practices in order to improve performance (Georgy et al. 2005; Elwakil et al. 2009). However, most modeling techniques in previous studies do not capture overall organizational competency and performance. Table 2.1 presents a summary of advantages and limitations of past competency and performance modeling methods.

The majority of competency and performance modeling methods presented in Table 2.1 are statistical and regression models, which are deterministic that cannot capture subjective uncertainty, complex and nonlinear relationships inherent in construction, which makes accurate predictions difficult. Thus, hybrid NFS that combine the learning power of ANN and functionality of fuzzy systems has been utilized previously in past studies to develop an accurate predictive model. In the following section, the review of NFS modeling technique and its application in construction, with a specific focus on modeling organizational competencies and performance is presented.

Table 2.1. Advantages and limitations of past competency and performance modeling methods

Method and References	Advantages	Limitations
Conceptual models Ahadzie et al. (2009, 2014); Boucher et al. (2007); IPMA (2006, 2015); PMI (2007); Salajeghe et al. (2014); Suhairom et al. (2014)	▪ Clear distinction between competency and performance ▪ Map competencies to performance	▪ Limited to specific aspects that do not capture organizational aspects ▪ Lack evidence-based relation; hence, needs validation
Statistical and SEM models Altuncan and Tanyer (2018); Bolivar-Ramos et al. (2012); Cheng et al. (2007); Dainty et al. (2004, 2005)	▪ Develops empirical evidence of the effects of competencies on organizational learning and innovation ▪ Demonstrate how competencies influence organizational performance	▪ Relates only top management support and technological skills to organizational performance ▪ Survey data based on self-reports from top management; hence, may be subject to bias ▪ Lacks context
Correlation and/or Regression models Levenson (2006); Liang et al. (2013); Ling (2002); Ling (2004); Liu et al. (2010); Subramanian et al. (2009)	▪ Captures relationships between competency and performance ▪ Establishes causal link between competencies and performance ▪ Predicts performance using competencies	▪ Generic and developed with limited data; hence, difficult to generalization ▪ Self-reports measures used for modeling cast doubts about findings
ANN models Elwakil et al. (2009)	▪ Captures complex relationships ▪ Captures both subjective and objective measures ▪ Possesses learning capability ▪ Predicts organization performance based on critical success factors (CSFs) ▪ Developed for construction organizations	▪ Considers CSFs instead of competencies ▪ Model output is performance measures in terms of CSFs. ▪ Do not capture uncertainty which is common in construction
FES (Fuzzy Logic) models Poveda and Fayek (2009)	▪ Represent conditional relationships i.e., rule-based knowledge ▪ Uses linguistic terms to assess the degree of interactions ▪ Capture expert knowledge on casual factors	▪ Lacks learning capability ▪ Model input factors consider only behavioral aspect of competency ▪ Developed with limited data
Hybrid Fuzzy Models Georgy et al. (2005), Georgy and Chang (2005), Omar and Fayek (2016)	▪ Models complex competency-performance relationships ▪ Captures both subjective and objective measures ▪ Possesses learning capability	▪ Lack model flexibility for varying contexts

2.4 Neuro Fuzzy Systems

A comprehensive literature review and detailed content analysis on NFS was conducted to identify and categorize NFS modeling techniques in CEM application, identification of evaluation criteria to investigate suitability of a particular NFS technique to a given CEM application, and recommend a suitable subset of NFS approaches for different construction applications. More details about the classification of NFS for construction applications, evaluation criteria of NFS, comparison of different NFS suitability to solve construction problems, and recommendation of NFS techniques for CEM applications can be found in Tiruneh et al. (2020). In this section, different NFS modeling techniques and their applications in construction are reviewed, their limitations established, and the rationale for selecting the proposed NFS modeling method for organizational competencies and performance are presented.

2.4.1 General Background on NFS

NFS has emerged as a dominant technique in modeling and solving complex real-world problems, and it has attracted the growing interest of researchers in various business, scientific, and engineering application areas because of its effective learning and reasoning capabilities (Chen et al. 2018; Georgy et al. 2005; Shihabudheen and Pillai 2018; Tokede et al. 2014). NFS are hybrid models that combine the learning power of ANN and functionality of fuzzy systems (i.e., improving reasoning and inference and explicit knowledge representation) (Aydin and Kisi 2015; Chan et al. 2009; Shihabudheen and Pillai 2018). There are different ways of combining fuzzy systems and ANNs such as a fuzzy-neural network (FNN) equipping a neural network to execute fuzzy information or NFS developed through augmenting neural networks in a fuzzy system (Jin 2010, 2011; Mitra and Hayashi 2000; Vieira et al. 2004). The resulting NFS perform better than any single method alone and is suited to handle real-world problems in a practical and effective manner taking advantage of complementary characteristics of ANNs and fuzzy systems (Chan et al. 2009; Chen et al. 2018; Georgy et al. 2005; Kar et al. 2014; Rajab and Sharma 2018). Knowledge representation, automated learning, and ability to use linguistic variables to model the input–output relationships of a given system makes NFS a powerful technique to solve complex real-world problems (Chen et al. 2018; Georgy et al. 2005; Shihabudheen and Pillai 2018).

2.4.2 Previous State of the Art Review Conducted on NFS

A wide range of survey papers on NFS are available for various application areas. For instance, Shihabudheen and Pillai (2018) conducted a comprehensive survey on recent advances in NFS. The study presents different classification methods of NFS based on learning algorithm (gradient, hybrid, population, extreme learning machine (ELM), and support vector machine (SVM)), fuzzy techniques (type-1 and type-2), and structure (Shihabudheen and Pillai 2018). A review of NFS applications in business is presented in Rajab and Sharma (2018). Mitra and Hayashi (2000) conducted an exhaustive survey on neuro-fuzzy rule generation that explains different ways to integrate fuzzy logic and neural networks for rule generation. Veira et al. (2004) presented a brief survey that classified NFS as cooperative, concurrent, and hybrid. Sahin et al. (2012) conducted a survey of hybrid expert systems including NFS that classifies NFS based on their structure, algorithm, application, and building/implementation tools. Kar et al. (2014) presented a review of the different applications of NFS such as student modeling system, electrical and electronics system, economic system, feature extraction and image processing, manufacturing, forecasting, medical system, and traffic control. Viharos and Kis (2015) presented a detailed survey of neuro-fuzzy applications in technical diagnostics and measurement.

According to Kar et al. (2014) it is difficult to collect, study, and classify the concerned articles since research work on NFS is distributed over a wide domain. Despite the abundance of published articles focusing on NFS topics, there are only few studies in the construction domain. Furthermore, studies dedicated to bibliometric or content analysis have not been done in the construction domain. Therefore, this section specifically focuses on NFS techniques used in construction applications, and it helps address the lack of a systematic review and content analysis of literature on these topics.

2.4.3 Application of NFS in Construction

Real-world problems in CEM are characterized by their non-specificity, uncertainty, complexity, dynamism, and non-linearity (Aydin and Kisi 2015; Chan et al. 2009). NFS combines knowledge representation with the learning power of ANN, consequently enabling it to represent qualitative, vague, and imprecise concepts (Chan et al. 2009). Thus, NFS possess a significant potential for a variety of applications in construction owing to its robust, fast, and effective characteristics for solving complex problems. As a result, NFS has been one of the most popular prediction modeling techniques capable of input-output mapping of complex and nonlinear relationships widely used successfully for various construction applications (Shahtaheri et al. 2015; Tiruneh et al. 2020). For instance, Jin (2010, 2011) applied the most commonly used NFS, ANFIS, for the decision-making process of efficient risk allocation. Elmousalami (2020) showed the suitability of computational intelligence (CI) techniques, which combine fuzzy logic, neuro computing, and evolutionary computing for parametric cost prediction models. Tokede et al. (2014) developed a neuro-fuzzy hybrid cost model for predicting the final cost of small water infrastructure project. Shahhosseini and Sebt (2011) proposed ANFIS for selecting and assigning employees for construction projects based on competency. Shahtaheri et al. (2015) developed an ANFIS-based model for estimating baseline rates for on-site work categories in the construction industry. Rashidi et al. (2011) used ANFIS and neuro-fuzzy genetic system for decision making to select construction project managers in line with project conditions and company priorities. Polat et al. (2014) developed ANFIS-based bid/no bid decision model. Azadeh et al. (2017) proposed an adaptive intelligent flexible algorithm composed of ANFIS, radial basis function (RBF), and multi-layer perception (MLP) for performance assessment and optimization of a pipe manufacturing factory. Furthermore, NFS is effectively used for many construction applications such as predicting compressive strength of concrete (Siraj et al. 2016), cost estimation (Wang et al. 2017), and multi-criteria decision making (Cheng and Roy 2010; Tavana et al. 2016). Thus, a review of past studies in general and the discussion made in this section indicates extensive application of NFS techniques for real-world construction problems.

2.4.4 Application of NFS for Modeling Organizational Competency and Performance

Although NFS has been emerged and proven to be very effective for a wide range of construction applications, there has been very few uses in modeling competency and performance. For instance, Omar and Fayek (2016) proposed a FNN to model construction project competencies and performance. The study showed that project performance can be improved by enhancing construction project competencies (Omar and Fayek 2016). Georgy et al. (2005) utilized neuro-fuzzy intelligent systems for estimating or predicting engineering performance in a construction project. Cheng et al. (2015) employed evolutionary fuzzy SVM to predict productivity loss. Cheng et al. (2012) used evolutionary fuzzy hybrid neural network for dynamic project success assessment in construction industry. Most studies except Omar and Fayek (2016), focus on performance prediction using various factors other than competency. NFS modeling techniques can explicitly represent and model the input–output relationships of complex problems and non-linear systems, such as predicting performance (Tiruneh et al. 2020). Thus, there is still a great potential in using NFS for modeling organizational competencies and performance capable of analyzing organizational competencies, relate them to performance and predict organizational performance.

2.4.5 Integrating NFS and Evolutionary Optimization Techniques

NFS modeling techniques such as ANFIS has been one of the most popular prediction models capable of input-output mapping of complex and non-linear relationships, and it's been widely and successfully used for various construction applications. ANFIS is a class of adaptive networks composed of two classes of nodes: adaptive nodes and fixed nodes (Acampora et al. 2014). Adaptive nodes are characterized by a collection of modifiable parameters, called a *parameter set*, whereas fixed nodes only deal with unmodifiable parameters (Acampora et al. 2014; Kumar and Hynes 2020). Adaptive networks are multi-layered feedforward structures whose overall output behavior is determined using the value of a collection of modifiable parameters (Kumar and Hynes 2020; Siraj et al. 2016; Tiruneh et al. 2020). Adaptive networks achieve a desired input–output by updating the parameter sets according to given training data (Acampora et al. 2014; Elbaz et al. 2019, 2020; Kumar and Hynes 2020). Figure 2.1 depicts the architecture of a typical ANFIS, which has two inputs, each with two MFs; two rules; and one output. The two fuzzy rules can be expressed as: If x is A_i, and y is B_i, then c is Z_i.

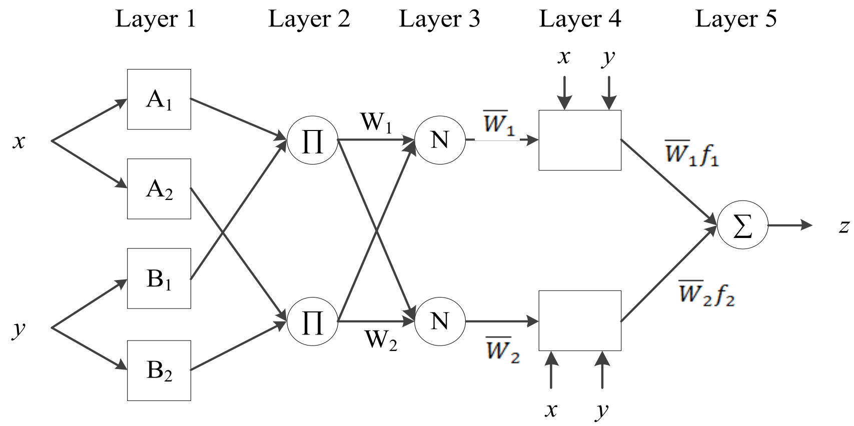

Figure 2.2. Basic architecture of ANFIS

NFS models such as ANFIS have good performance with desirable accuracy compared to the conventional mathematical or regression models in real engineering practice (Yuan et al. 2014). However, there has been an argument as to whether ANFIS can yield reasonable solutions with robustness since AI models still suffer from local minima and poor generalization (Elbaz et al. 2020; Rini et al. 2016; Yuan et al. 2014). As a result, it may lead to provide less accurate results and/or distorted/inadequate explanations for problems (Elbaz et al. 2019, 2020). To overcome these limitations, ANFIS needs to be optimized with EA techniques (Elbaz et al. 2019, 2020). EAs such as GA, PSO, ABC, ACO etc. have been widely used for optimization owing to their ability in searching for optimal solutions in an irregular and high dimensional solution space (Eftekhari and Katebi 2008). EAs are population-based algorithms which allow for the simultaneous exploration of different parts of the search space and achieve multiple optimal solutions (Rini et al. 2016).

Integrating EAs with other AI methods such as NFS in engineering problems leads to increased accuracy (Kamarian et al. 2014; Qasem et al. 2017). Furthermore, hybridizing of a robust optimization algorithm such as GA with NFS provides a scope to improve the effectiveness of

MFs and fuzzy rules in the model (Elbaz et al. 2019, 2020; Karaboga and Kaya 2019). It has been observed that there is a trend toward EA based training algorithms for better performance of NFS models in recently published studies (Elbaz et al. 2019, 2020; Karaboga and Kaya 2019; Tiruneh et al. 2020). Thus, in this research GA is implemented for optimizing the NFS model.

2.4.6 Application of Hybrid NFS in Construction

Recent studies showed that combining conventional NFS with other modeling techniques or optimization algorithms enables achieving an improved performance of the resulting model. For instance, Golafshani et al. (2020) used ANN and ANFIS hybridized with the grey wolf optimization (GWO) for predicting compressive strength of normal and high-performance concrete. Likewise, Yuan et al. (2014) proposed GA-ANFIS for predicting concrete compressive strength. Pamučar et al. (2016) used ANFIS with ABC optimization for decision making related to cost and risk aggregation in multi-objective route planning. Nazari and Sanjayan (2015) proposed a hybrid model based on ANFIS and imperialist competitive algorithm (ICA) capable of predicting the compressive strength of ordinary portland cement (OPC) based geopolymers. However, literature on application of hybrid of EAs and NFS for modeling organizational competencies and performance are very few. Elbaz et al. proposed a hybrid GA-ANFIS (Elbaz et al. 2019) and PSO-ANFIS (Elbaz et al. 2020) model to predict performance for tunneling projects.

Although many studies indicated that EAs had significant ability in performance improvement of NFS for prediction, the application of hybrid NFS in construction research has still limitations in handling multiple outputs. The configuration of most of the NFS architectures e.g., ANFIS shown in Figure 2.1 is only suitable for MISO problems. As such, there remains a need for developing a modeling approach that can improve NFS so that it can handle complex and nonlinear MIMO

CEM problems. Thus, a novel methodology for developing a modeling approach that combines NFS (i.e., MANFIS) and GA capable of handling MIMO problems is developed in this research to model construction organizational competencies and performance. The following section provides an overview and applications of MANFIS modeling techniques.

2.5 MANFIS Modeling Techniques

Many real-world engineering problems, particularly in construction, are complex and non-linear MIMO systems (Acampora et al. 2014; Fattahi et al. 2018), in which the system's multiple output variables may each depend on all input variables (Acampora et al. 2014). This strong dependence among variables leads to highly complex and dynamic systems that make MIMO models too imprecise and uncertain to be trained using conventional system modeling approaches (Acampora et al. 2014; Fattahi et al. 2018). However, because conventional NFSs are configured as MISO systems (e.g., ANFIS) and therefore have limitations in handling MIMO systems (Acampora et al. 2014; Cheng et al. 2002), various approaches have used improved ANFIS methods for learning the behavior of MIMO systems, such as MANFIS (Acampora et al. 2014; Benmiloud 2010; Cheng et al. 2002; Das and Winter 2016; Nayak et al. 2015). MANFIS can be viewed as an aggregation of many independent ANFISs and capable of modeling highly non-linear and complex systems (Cheng et al. 2002; Das and Winter 2016; Nayak et al. 2015). The core of the proposed framework is a processing layer that contains ANFIS modal blocks that each corresponds to and predicts a single output, as shown in Figure 2.2 (Benmiloud 2010; Cheng et al. 2002; Das and Winter 2016; Malik and Arshad 2011).

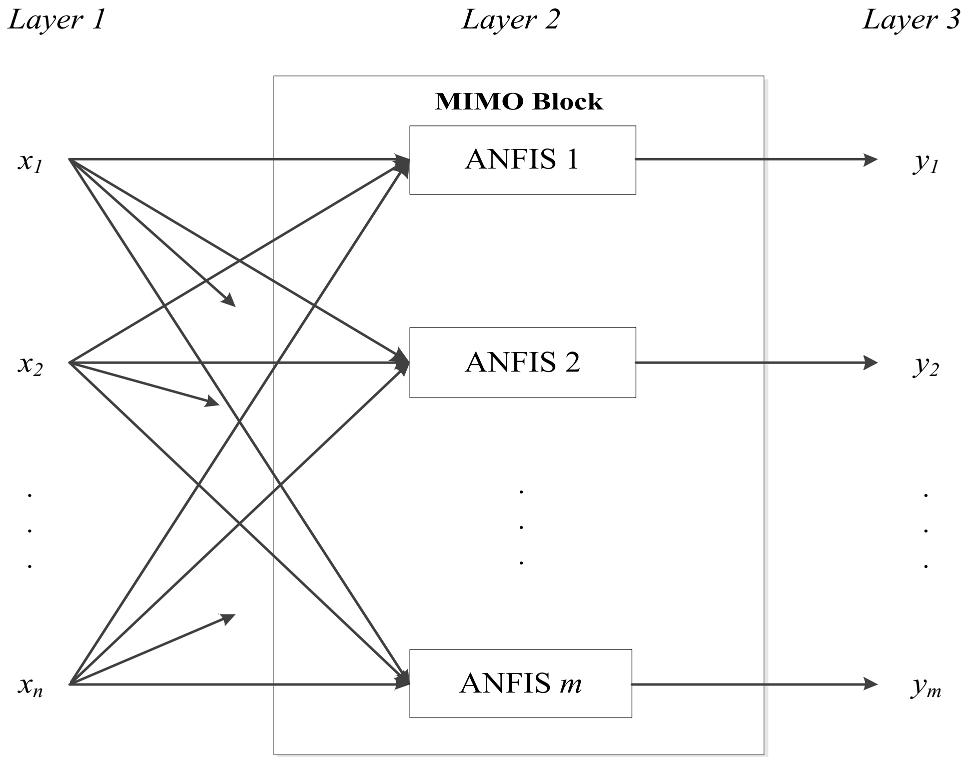

Figure 2.3. Basic architecture of MANFIS

Past studies that used MANFIS showed its good performance in approximating multiple outputs with the desired precision simultaneously (Benmiloud 2010; Das and Winter 2016; Malik and Arshad 2011; Nayak et al. 2015). Benmiloud (2010) confirmed the performance of MANFIS in predicting multiple outputs with the desired accuracy. Malik and Arshad (2011) proposed a MANFIS to model the multivariable primary pressure control system of a nuclear power plant that predict control valve positions with the highest accuracy. Das and Winter (2016) presented a MANFIS model that predicts multi-output urban transport modes (bus, train, tram, and walking) with high accuracy. Agah and Soleimanpourmoghadam (2020) developed a MANFIS model to predict the existence of pollutant heavy metals in the environment that predicts the concentration of four heavy metals in mine drainages with high accuracy. Furthermore, MANFIS does not need a lot of manual configuration because the parameters are adjusted through the learning and/or optimization process, based on input data (Nayak et al. 2015). However, the choice of clustering method for input data is critical, because it can impact the number of rules and the generalization power of the model (Fattahi et al. 2018; Nayak et al. 2015). For instance, Fattahi et al. (2018) showed the impact of clustering method comparing the results of three MANFIS prediction models based on grid partitioning, subtractive clustering, and fuzzy *c*-means (FCM) clustering. The comparison showed that subtractive clustering and FCM clustering provided a comparable predictive accuracy. However, studies recommend using FCM to avoid an exponential growth of rules due to the number of input variables. The learning process of the MANFIS network terminates when the error measure is reduced to a designated threshold level and therefore the desired mappings between the independent variables and the outputs are obtained (Cheng et al. 2002). MANFIS has similar limitations that ANFIS has (i.e., slow computational convergence and potential of being trapped in local minima), which results in low accuracy and poor generalization. Using a hybrid of MANFIS and evolutionary optimization techniques, such as GA, PSO, ABC, and ACO, is vital to improving MANFIS performance.

Optimization of a multi-output system is performed by integrating a MANFIS network and various EAs such as GA to improve the prediction capacity (Cheng et al. 2002). For instance, Cheng et al. (2002) proposed a hybrid MANFIS neuro-fuzzy network that uses GA to optimize multiple-objective decision-making problem. Tahmasebi and Hezarkhani (2012) investigated the performance of integrated neural-fuzzy and GA (GA–ANFIS) for MIMO problems to predict the ore grade from the boreholes of copper deposits. The result showed that their proposed approach has an excellent performance for grade estimation (Tahmasebi and Hezarkhani 2012). Review of past studies shows that very few studies have focused on MANFIS in general and incorporating

EA methods, especially GA. As a result, this research developed a hybrid of GA and MANFIS to develop a model that predicts organizational performance using organizational competencies. Thus, the GA-MANFIS model developed in this research enables construction organizations to identify and evaluate their competencies that have significant impact on performance and to predict multiple organizational performances simultaneously.

2.6 Chapter Summary

This chapter provided a brief literature review on concepts related to organizational competencies and performance. A review of literature revealed that many past studies emphasize only select aspects of competency, such as individual/personal or project-level competencies, while competency studies at the organizational level are few. In this chapter, the existence of a positive relationship between organizational competency and performance has been established. Also, the literature review indicated that there is a lack of systematic review and content analysis of published articles related to organizational competencies and performance.

In this chapter, an overview of organizational competency and performance modeling methods employed in construction applications are presented. Different modeling methods for organizational competency and performance were discussed and their respective advantages and limitations were presented. Despite availability of wide array of robust modeling techniques, only few are commonly used in construction applications in general and specifically for modeling competencies and performance. Most of the models discussed in published articles are statistical and regression deterministic models that cannot capture subjective uncertainty, complex and nonlinear relationships inherent in construction. To address these limitations, some efforts have been made to integrate fuzzy systems (fuzzy logic) and ANNs; hence, NFS. Conventional NFS have limitations related to slow computational convergence and potential of being trapped in local minima that may provide less accurate results and poor generalization. Thus, efforts made to integrate NFS and EAs in construction (i.e., to improve accuracy and generalization capability) were examined and limitations were established. Accordingly, most of conventional and hybrid NFS such as ANFIS fails to directly deal with MIMO systems due to their MISO structure. Thus, an overview of MANFIS modeling techniques that can handle MIMO problems was explored. The next chapter presents results of the focus group study on organizational competencies and performance measures in construction.

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Chapter 3 Competency and Performance Measures for Organizations in the Construction Industry: Content Analysis and Focus Group Study[3]

3.1 Introduction

Organizational competency is as an integrated combination of resources, particular sets of skills, necessary information, technologies, and the right corporate culture that enable an organization to achieve its corporate goals, competitive advantage, and superior performance (Tiruneh and Fayek 2018, 2020). However, many past studies emphasize only select aspects of competency at individual/personal or (Salajeghe et al. 2014) project level (IPMA 2006,2015; Hanna et al. 2016, 2018; Omar and Fayek 2016; Salajeghe 2014). However, competency studies at the organizational level are few (Edgar and Lockwood 2008; Escrig-Tena and Bou-Llusar 2005; Sparrow 1995). Although organizational competency is a major research focus in many disciplines such as business, human resources, and management, limited research has been conducted in the construction domain. Competency studies at an organizational level need to account for the unique nature of construction, which is widely regarded as complex, full of uncertainties, and contingent on changing environments. As such, there remains a need for a comprehensive analysis of all aspects of organizational competencies that improve performance for construction organizations operating in a highly competitive global market. Thus, this chapter has the following objectives:

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(1) to conduct an extensive review and detailed content analysis on organizational-level competency and performance studies in the construction domain; (2) to identify and systematically categorize organizational competency and performance measures; (3) to evaluate, rank, refine, and validate the list of organizational competency and performance measures and their categorization.

The rest of this chapter is structured as follows. First, the research methodology adopted in this chapter is discussed and provides the outcomes of the content analysis. Second, the results and discussion of the focus group findings are presented. Third limitations of the focus group results are explained. Finally, a summary of this chapter is provided.

3.2 Research Methodology

The research methodology for this study had three major stages. First, relevant articles from highly regarded journals mostly in construction research were selected. Then, a comprehensive literature review and detailed content analysis was conducted to identify and categorize organizational competency and performance measures. Finally, a focus group study was carried out to evaluate and rank identified competency and performance measures and validate their categorization. The detailed procedures of the research methodology are presented below.

3.2.1 Selection of Journals and Relevant Articles

In stage 1, journals that are highly-ranked in the construction engineering and management research community were selected. Scopus, a powerful search engine that includes most research publications in construction, engineering, management, and business, was initially used. However, most of the competency studies—including those published earliest—were from business, human resources, and management studies; therefore, journals outside the construction domain were also considered for selection. Thus, to maximize the coverage of journal coverage focusing on competency studies, databases that provide highly-ranked and relevant research work were also used, such as the American Society of Civil Engineers (ASCE) library, the *International Journal of Project Management* (IJPM) database, Elsevier, Emerald, Taylor & Francis Online, the Wiley Online Library, and Scopus. Journals that have a CiteScore of 0.90 and above according to 2017 Scopus journal metrics were considered.

The search for relevant articles was restricted to articles published between 1985 and 2018 and conducted using the title, abstract, and keywords (T/A/K) field of the above bibliographical sources. Then, articles relevant to the study were selected using appropriate search terms, including "competency", "performance measurement", "organizational competency", "organizational performance", "competency and performance measures", and "organizational competency and performance measures". As a result, 354 articles focusing on competency and performance from 50 journals were initially identified. The contents of the articles were further examined, and the number of articles was reduced to 125 from 33 journals. The complete list of selected articles used for the content analysis is provided in Appendix A. Articles were selected based on the following criteria: (1) the article should focus on competency and performance in general and on construction in particular; (2) the article should mention, discuss, or list competency and performance measures; and (3) the article should use a specific classification and categorization technique of competency and performance measures. The 354 articles were considered to have met the initial requirement for further analysis since the search terms appeared in the titles, abstracts, or keywords. Due to widespread use of the search terms used for this chapter in CEM research, the abstract of each article was used to filter out irrelevant papers for the content analysis (Chan et al. 2009; Yi and Chan 2014). Therefore, articles that included any of the search terms in their titles, abstracts, or keywords but that did not focus on topics related to discussing, classifying, and categorizing competency and performance measures were excluded. Thus, the 354 articles were reduced to 125. Of the 125 articles considered, 108 (86%) of the articles were from 16 journals that each include at least three articles. The largest number of articles selected were from the following journals: *Construction Management and Economics* (17 articles), *Expert Systems with Applications* (8 articles), *International Journal of Project Management* (10 articles), *Journal of Construction Engineering and Management* (9 articles), *and Journal of Management in Engineering* (7 articles). The remaining 17 articles from 17 journals listed in Appendix A were included because of their relevance to the objectives of this chapter based on the article selection criteria.

3.2.2 Content Analysis

A comprehensive review of articles selected in stage 1 was conducted to identify relevant articles that focus on competency and performance for content analysis. Content analysis is a robust technique for collecting and organizing information in order to examine trends and patterns and determine major facets of and valid inferences from analyzed documents (Siraj and Fayek 2019). Content analysis can be qualitative or quantitative. Qualitative content analysis focuses on grouping data into categories based on the contents. Quantitative content analysis determines the numerical values of categorized data (i.e., frequencies, ratings, and rankings) by counting the number of times a topic is mentioned (Chan et al. 2009; Siraj and Fayek 2019). In this chapter, a combination of qualitative and quantitative content analysis was adopted in order to (1) review recent advances in competency and performance studies applicable to the construction domain, (2) develop a comprehensive list of competency and performance measures; (3) identify and examine common competency and performance measures and their categorization methods, and (4) systematically identify and categorize the most commonly used organizational competency and performance measures. As a result, a comprehensive list of organizational competency and performance measures was identified and the measures were categorized, as presented in the following section.

3.2.3 Identification and Categorization of Organizational Competency and Performance Measures

3.2.3.1 Identification and Categorization of Organizational Competency

According to Campion et al. (2011), competencies can be hierarchically arranged into categories and subcategories to simplify their presentation for the user, especially if there are a large number of competencies. By performing content analysis and conducting a comprehensive review of the literature, 18 commonly used competency categories were identified. These competency categories were further reduced to 12 by merging categories to avoid redundancy and similarity. In addition, the content analysis indicated that competencies have been viewed from two different perspectives: (1) as assets, skills, or resources belonging to the company that allow an activity to be performed systematically; and (2) as the activities themselves, that is, the operations that the firm is able to carry out by integrating a series of assets, emphasizing what the company does as opposed to what the company has (Escrig-Tena and Bou-Llusar 2005; Omar and Fayek 2016; Succar et al. 2013; Walsh and Linton 2001). The first perspective identifies the cognitive aspect, which is related to the knowledge and skills the firm possesses (i.e., behavioral competencies); the second perspective identifies the processes and practices of implementing the activities, functions, and/or operations the firm undertakes (i.e., functional competencies). Accordingly, 157 competencies were identified and grouped into two sets of organizational competencies: functional (how the organization operates and functions) and behavioral (individual/organizational attributes). The list of competencies was further refined to avoid redundancy and similarity. For instance, competencies described as strategic thinking, strategic planning, strategic policy, and strategic management were merged into one competency. As a result, a total of 101 competencies (i.e., 58 functional and 43 behavioral competencies) were selected and grouped under 12 categories, as shown in Table 3.1. The competency categories that already exist in the literature are limited to a select few aspects of competency, such as individual/personal, managerial, and cost estimation competencies. In contrast, the categorizations of organizational competencies proposed in this chapter capture an overall view of organizational processes and practices. Therefore, this chapter categorizes organizational competencies hierarchically that considers how the organization operate their functions and organize their resources especially human resources.

Functional competencies are the technologies, abilities, and knowledge necessary to perform work-related tasks effectively and to produce specific desired outcomes within the functional domains of the organization (Loufrani-Fedida and Missonier 2015; McDermott 2003). In line with past studies and taking into account construction organizational operations, a total of 58 identified functional competencies are organized into seven categories based on specialized functional areas or departments (e.g., general administration, production/operations, project management, and construction and engineering research and development) and those spanning intra-organization or interdisciplinary functional domains (i.e., cross-functional, technical, and supervisory/managerial competencies).

Table 3.1. Organizational competencies

Group	Competency category	No. of competencies	Competencies (No. of articles that cite the competency)
Functional	General administration	5	Staff development/training (22); human resources/personnel management (22); results orientation (5); goal orientation (5); managing and support of diversity (8)
	Technical	9	Quality of work (22); technical/job knowledge (19); commitment to safety (6); planning and organizing (10); strategic planning and management (20); attention to detail (3); business acumen/business management skills (13); market management (12); finance management (13)
	Cross-functional	5	Cooperation and coordination (collaboration) (13); stakeholder focus (26); communications management (16); delegation (3); public and government relations (5)
	Production/operation	6	Construction technology/integration management (9); operations and maintenance (5); process engineering management (17); construction, production, and manufacturing (8); materials management (5); product engineering (7)
	Construction and engineering research and development	4	Business, legal, and public policy (3); construction law and regulation (3); management information systems/technology (22); new technology/product development (17)
	Project management	24	Safety, health, security, and environment (13); quality management (15); schedule (time) management (15); scope management (5); change management (11); managing performance (4); cost management (8); commissioning and start-up (3); project monitoring and controlling (3); project resource management (5); risk management (15); design development (3); integration management (7); project materials management (5); stakeholder management (5); contract administration (4); project communications management (6); environmental management (3); team building (12); procurement management (8); project human resource management (9); program management (3); conflict management (6); commitment to sustainability (3)
	Supervisory/managerial	5	Values and ethics (3); engagement (5); management excellence (3); resource management (5); strategic thinking (3)

Group	Competency category	No. of competencies	Competencies (No. of articles that cite the competency)
	Subtotal	**58**	
Behavioral	Organizational attributes	7	Ability to build trust (5); competitiveness (3); adaptability/flexibility (27); achievement drive (27); innovation (30); organizational awareness, culture, and values (9); risk-taking (5)
	Top management	4	Leadership (26); strategic thinking (9); judgement (5); analytical ability (14)
	Middle management	7	interpersonal skills (15); decision-making (15); consultation (4); negotiation (8); reasoning (3); conflict and crisis resolution/issue management (13); assertiveness (6)
	First-line management	8	Problem-solving (6); integrity/high standards (4); planning and organizing (8); results orientation (3); responsiveness (3); influence (12); communication (20); incisiveness (3)
	Individual/personal	17	Reliability/dependability (8); teamwork (17); ethics (4); initiative (14); commitment (5); effectiveness (8); self-regulation/control (16); motivation (10); resourcefulness (3); perseverance (3); attention to detail (4); professionalism (9); cognitive skills (6); self-confidence (10); creativity (11); sales mindset/selling skills (3); enthusiasm (3)
	Subtotal	**43**	
	Total	**101**	

Behavioral competencies are the individual or organizational attributes that enable the effective and consistent execution of organizational functions, thereby ensuring market competitiveness (IPMA 2006; Rosas et al. 2011). Forty-three behavioral competencies are arranged in five categories according to organizational hierarchy and managerial levels. The first competency category deals with the overall organizational attributes that identify a given construction organization as a single entity. The managerial attribute competencies are grouped into top, middle, and first-line management competencies. Individual/personal attributes make up the fifth behavioral competency category, which encompass competencies that are important for all sets of individuals in the organization.

3.2.3.2 Identification and Categorization of Organizational Performance Measures

In this chapter, a total of 44 organizational performance measures and classified them as KPIs, KPOs, and PerMs. Performance measures can be either leading indicators (KPIs), lagging indicators (KPOs), or both (PerMs). KPIs are made up of five categories (i.e., cash flow, quality of work, market shares, safety, and financial stability). The performance measures under the KPI categories are leading indicators that enable the prediction of future trends and identify problems in the early stages of organizational operations and/or projects, which provides the opportunity for intervention to improve performance. KPOs are made up of four categories (i.e., profitability, growth, business efficiency, and effectiveness of planning). The performance measures under the KPO categories are lagging indicators, which are measured as a result of an outcome and which do not enable change. PerMs are categorized as internal customer satisfaction, external customer satisfaction, or competitiveness, dependent on the manager's/individual's perception and/or focus. PerMs can be either leading or lagging indicators, depending on when they are measured. The full list of identified organizational performance measures and their categories is shown in Table 3.2.

Table 3.2. Organizational performance measures

Group	Category	No. of performance measures	Performance Measures (No. of articles that cite the performance measure)
KPIs	Cash flow	1	Cash flow (5)
	Quality of work	2	Rework factor (4); prevention, appraisal, and failure (PAF) model (3)
	Market share	2	Market returns (3); market share (11)
	Safety	5	Incident rate (4); time lost (4); safety performance (4); accident frequency rate (5); accident cost (3)
	Financial stability	2	Debt ratio (4); liquidity (3)
	Subtotal	**12**	
KPOs	Profitability	10	Profitability (13); return on investment (5); return on capital (3); return on assets (8); net income (3); return on equity (3); economic value added (3); return on sales (5); financial autonomy (3); hanging invoice (3)
	Growth	3	Revenue growth (9); sales growth (9); volume of works growth (7)
	Business efficiency	2	Net profit margin (3); efficiency ratio (2)
	Effectiveness of planning	5	Cost predictability (5); time predictability (5); change cost factor (3); cost growth/increase (4); time growth/increase (4)
	Subtotal	**20**	
PerMs	Internal customer satisfaction	5	Employee satisfaction (8); employee turnover rate (2); average remuneration per employee (2); profit per employee (2); turnover/revenue per employee (2)
	External customer satisfaction	4	Customer satisfaction (13); customer retention/loyalty (3); percentage of repeat customers (2); number of complaints (3)
	Competitiveness	3	Company image/reputation; (6) competitive advantage (3); market advantage (2)
	Subtotal	**12**	
	Total	**44**	

3.2.4 Focus Group

In stage 3, a focus group study was conducted to evaluate, rank, refine, and validate the list of organizational competency and performance measures and their categorization, which were identified through extensive literature review and detailed content analysis. A focus group consists of a group discussion with a moderator prompting the participants to exchange ideas and explore expert opinions based on the participants' experiences (Leung et al. 2014).

The focus group study, approved by the University of Alberta Human Research Ethics Board, was conducted in two phases: the focus group survey and the focus group discussion. The first phase consists of a focus group survey, where participants evaluate the list of organizational competency and performance measures based on their importance with respect to their respective categories. A five-point importance scale was used for evaluation (i.e., extremely unimportant, unimportant, neither unimportant nor important, important and extremely important). The second phase was the focus group discussion session with five discussion points. An interactive semi-structured focus group discussion led by two moderators/facilitators was conducted. The moderators encouraged the participants to exchange ideas and describe their experiences pertaining to identifying, measuring, and evaluating competency and performance in their organizations.

3.2.4.1 Size of the Focus Group

An invitation to participate in the focus group study was sent out via email to individuals working in the construction industry, through eight member organizations of an industry-based research partnership program involving a wide range of company types operating in the construction industry, such as owners, contractors, consultants, trades. Some of these members organizations are associations, who sent out the invitation to their members. A purposive sampling was adopted, in which participants had to fulfill at least the following criteria: (1) they all had either a managerial or senior position and had experience and knowledge of how organizations operate in the construction industry so they could effectively evaluate the competency and performance measures at the organizational level and (2) they were still actively working and had at least five years of practical experience in organizations and/or projects in the construction industry. The purposive sampling that was adopted helped to ensure both the quality of data collected and a mix of wide-ranging interdisciplinary participants (Leung et al. 2014).

There were 13 participants in the focus group study representing eight organizations operating in the construction industry. The North America Industry Classification System (NAICS) – Canada published by Statistics Canada (2017) was used to determine the construction industry sector categories. The participants' demographic information is presented in Table 3.3. The participants of the focus group were highly experienced professionals (the majority are 40 years old and above with an average work experience of 20 years or more) who hold a management position in their respective organizations. As practitioners working in the construction industry, participants provided their expert opinion in the focus group discussion on issues applicable to their specific organizations. The participants represented eight companies, the majority of which (five) are owner companies involved in heavy and civil engineering construction, specifically in the energy (i.e., oil and gas, and power) sector. Of the three remaining companies, one of them is a general contractor and two are specialty subcontractors. Of the eight companies represented, seven of them are large organizations with more than 300 employees and one is small with less than 50 employees.

Table 3.3. Focus group participants' demographic information

Background information	Categories	Number of participants
Age	18–30	0
	31–40	3
	41–50	6
	51–60	4
Company type	Owner	9
	General contractor	1
	Specialty/Subcontractor	3
Position	Senior management	5
	Project management	4
	Engineering management	1
	Project controls	1
	Product manager	1
	Construction manager	1
Overall years of work experience	<10	2
	11–20	5
	21–30	3
	31–40	3
Gender	Male	11
	Female	2

3.2.4.2 Focus Group Session Procedures

The focus group consisted of three parts: (1) introduction and presentation, (2) focus group survey evaluation, and (3) focus group discussion. At the beginning of the focus group, participants introduced themselves and stated their position and organization. The moderators described the purpose of the study and the function of the focus group (i.e., processes, procedures, and anticipated outcomes), the focus group rules (i.e., equal status and voice of each participant to provide suggestions), and confidentiality of the discussions. In addition, the moderators briefly presented the definitions of organizational competency and performance measures, the categories of competency and performance measures proposed based on the content analysis, and a planned framework to relate competencies to performance.

Participants were provided with two sets of documents. The first document was a focus group survey consisting of a list of organizational competencies classified as functional or behavioral and grouped under seven and five categories, respectively. This document also included organizational performance measures classified as KPIs, KPOs, and PerMs. Participants were asked to review the list and categorization of each competency and performance measure and evaluate it within its respective category, using a 5-point importance scale (1 = extremely unimportant and 5 = extremely important). As a reference, a second document consisting of the definitions of each organizational competency and performance measure was also provided to help participants understand and evaluate them effectively and validate their categorization.

Following the focus group survey, a semi-structured participative discussion was conducted. For the discussion session, the moderators provided five semi-structured open-ended questions to explore participants' experiences and opinions pertaining to identifying, evaluating, and validating the categorization of organizational competency and performance. The moderators made notes during the focus group discussion to capture participants' opinions and feedback. The moderators also facilitated the discussion by elaborating on and further explaining the suggestions and questions posed by participants. The explanations allowed the moderators and participants to cross-check their respective understandings of the ideas and opinions provided during the course of the discussion, thus helping to minimize data distortion and misrepresentation.

3.2.4.3 Focus Group Survey Data Analysis

All 13 focus group participants completed the survey. The Relative Importance Index (*RII*) for each of the competency and performance measures is calculated using Equation (3.1) to identify the importance of each competency or performance measure relative to the other competency or performance measures in a given category and to rank them accordingly (Gündüz et al. 2013).

$$RII = \frac{\sum_{i=1}^{5} a_i n_i}{AN} \tag{3.1}$$

where $a_i, i = 1, \dots, 5$, is a constant representing importance scales 1 to 5 (i.e., 1 representing extremely unimportant and 5 representing extremely important); n_i, is the number of respondents who selected importance scales of a_i; A is the highest score of the importance scale (i.e., 5); and N is the total number of respondents (i.e., 13) who participated in the focus group.

The *RII* value has a range of 0 to 1, where the higher the *RII*, the more important the competency and/or performance measure relative to the other competency or performance measures in the same category. *RII* helps to identify the most important competency and performance measures based on their values of *RII* and their ranking.

3.2.4.4 Focus Group Discussion Data Analysis

A participative discussion was conducted after the focus group survey was completed. The moderators posed a set of semi-structured questions to initiate full participation and interaction from all participants. The semi-structured questions asked were participants' opinions on the categorization of competency and performance measures; show gaps and provide recommendations for improving the proposed approach; feasibility of collecting data on competency and performance measures from various organizations using the proposed approach; and whether the proposed approach mirrors each participant's organization's approach to defining and measuring organizational competency and performance. The data collected from the discussion were encoded and analyzed in conjunction with the focus group survey data.

The purpose of the focus group was to evaluate and identify important competency and performance measures at the organizational level and refine the full list of competency and performance measures for future data collection and modeling. The relative importance of competency and performance measures was quantified using the *RII* and ranked accordingly within each respective category. To refine the list of competency and performance measures, 60 percent of the top-ranked competencies were selected for categories having ten or fewer competencies and 40 percent of the top-ranked competencies were considered for categories with more than ten competency or performance measures. If a category had fewer than five competencies or performance measures, all of them were selected. The rationale for applying these refining criteria was to provide a balanced number of competencies within each competency category.

3.3 Results and Discussion

3.3.1 Focus Group Survey Results

The focus group analysis is implemented following the approach presented in Gündüz et al. (2013). The complete list of ranked organizational competencies and performance measures based on the focus group survey analysis is provided in Appendix B.

3.3.1.1 Organizational Competencies

The results showing the *RII* values and the rankings of organizational competencies are provided in Appendices B.1 and B.2 for functional and behavioral competencies, respectively. The mean *RIIs* and the competency category rankings are discussed below. The three top-ranked competencies in each of the competency categories from Appendices B.1 and B.2 are discussed in the following sections, based on the mean *RII* and the ranking order of the competency categories.

A. Functional Competencies

Among the seven functional competency categories (Appendix B.1), the three top-ranked functional competency categories are supervisory/managerial competencies (*RII* = 0.874), production/operation competencies (*RII* = 0.867), and project management competencies (*RII* = 0.853), respectively. Cross-functional competencies (*RII* = 0.852) are the fourth-ranked competency category. The three lowest-ranked competency categories are construction and engineering research and development competencies (*RII* = 0.849), technical competencies (*RII* = 0.836), and general administration competencies (*RII* = 0.785), respectively.

i. Supervisory/managerial competencies (RII = 0.874)

The supervisory/managerial category is the top ranked functional competency category. *Values and ethics* (*RII* = 0.923) is the top ranked competency in this category. Values and ethics encourage adherence to the appropriate and effective core values, culture, and work ethic of the organization. *Engagement* and *management excellence* are the two second ranked competencies in this category, each with an *RII* of 0.877. Engagement helps supervisors and managers lead across organizational boundaries in order to unite a broad-based group of stakeholders, partners, and clients/customers in a shared agenda and strategy. Management excellence is critical for ensuring that people have the support and tools they need and that the workforce as a whole has the capacity and diversity to meet current and long-term organizational objectives.

ii. Production/operation competencies (RII = 0.867)

Production/operation is the second ranked competency category. In this category, *construction technology/integration management* and *operations and maintenance* are the two top ranked competencies, each with an *RII* of 0.908, followed by *process engineering management* (*RII* =

0.862). Construction technology/integration management helps to optimize specific activities and coordinate the diverse components of production, operation, and/or construction works through the application of current technology available in the industry. Operations and maintenance ensure awareness of procedures/systems and safety considerations for setup, process/procedures, control, maintenance, and improvement of technologies that support production, operations, and maintenance in order to meet stakeholder requirements. Process engineering management enables the planning and coordination of process development and improvement across the organization, by identifying and analyzing the strengths and weaknesses of each process relative to acceptable standards.

iii. Project management competencies (RII = 0.853)

Project management is the third ranked competency category. *Safety, health, security, and environment* (*RII* = 0.954) is the top ranked project management competency. *Quality management*, *schedule (time) management*, and *scope management* are the three second ranked project management competencies, each with an *RII* of 0.923. Organizations in the construction industry are largely project-based companies (Kwak et al. 2015; Deng and Smyth 2013; Lin and Shen 2007); thus, project management competencies play a critical role in organizational success and performance.

iv. Cross-functional competencies (RII = 0.852)

The fourth ranked category is cross-functional competencies. *Cooperation and coordination* (*RII* = 0.933) is the top ranked cross-functional competency; it enables the integration of various interdisciplinary functional domains that span an organization. *Stakeholder focus* (*RII* = 0.877) and *communication management* (*RII* = 0.867) are the second and third ranked competencies, respectively, in this category.

v. Construction and engineering research and development competencies (RII = 0.849)

Construction and engineering research and development is the fifth ranked competency category. The three top ranked competencies in this category are *business, legal, and public policy* (*RII* = 0.883), *construction law and regulation* (*RII* = 0.877), and *management information systems/technology* (*RII* = 0.850). Construction and engineering research and development competencies are vital for ensuring organizational work processes remain effective, and they help create innovative processes and products that give the company a short-term and long-term competitive advantage.

vi. Technical competencies (RII = 0.849)

The sixth ranked competency category is technical competencies. The first and second ranked competencies in this category are *quality of work* (*RII* = 0.969) and *technical/job knowledge* (*RII* = 0.954), respectively, which indicate the ability of an organization to execute its operations and projects with the desired quality and appropriate expertise. *Commitment to safety* (*RII* = 0.938) is ranked third in this category.

vii. General administration competencies (RII = 0.849)

The general administration competency category is the lowest ranked functional competency category. In this category, *staff development/training* and *results orientation* are the two top ranked competencies, each with an *RII* of 0.831. The third ranked competency in this category is *goal orientation* (*RII* = 0.800). Staff development/training addresses knowledge gaps by providing coaching, training, and continuous learning to help staff develop professionally and to support organizational improvement. Results orientation enables an organization to achieve expected results through successful and timely completion of organizational operations. Goal orientation helps identify short- and long-term organizational objectives and strategies, as well as how to use resources effectively and efficiently to achieve these goals.

B. Behavioral Competencies

Based on the mean *RII* and ranking shown in Appendix B.2, the three top ranked behavioral competency categories are top management competencies (*RII* = 0.900), organizational attributes (*RII* = 0.882), and first-line management competencies (*RII* = 0.877), respectively. Middle management (*RII* = 0.855) and individual/personal competencies (*RII* = 0.835) are the fourth and fifth ranked behavioral competency categories, respectively.

i. Top Management competencies (RII = 0.900)

The top ranked behavioral competency category is top management competencies. The three top ranked competencies in this category are *leadership* (*RII* = 0.969), *strategic thinking* (*RII* = 0.954), and *judgment* (*RII* = 0.846), respectively.

ii. Organizational attribute competencies (RII = 0.882)

The second ranked behavioral competency category is organizational attributes. The two top ranked competencies in this category are *ability to build trust* (*RII* = 0.933) and *competitiveness* (*RII* = 0.908), respectively. *Adaptability/flexibility* and *achievement drive* are both ranked third, each with and *RII* of 0.908.

iii. First-line management competencies (RII = 0.877)

The third ranked behavioral competency category is first-line management competencies. *Problem-solving* (*RII* = 0.938), *integrity/high standards* (*RII* = 0.908), and *planning and organizing* (*RII* = 0.892) are the three top ranked competencies, respectively.

iv. Middle management competencies (RII = 0.855)

Middle management competencies is the fourth ranked behavioral competency category. *Interpersonal skills* and *decision-making*, each with an *RII* of 0.923, are the two top ranked competencies in the category. *Consultation*, *negotiation*, *and reasoning* ranked third, with an *RII* of 0.923.

v. Individual/personal competencies (RII = 0.835)

Individual/personal competencies is the fifth ranked behavioral competency category. *Reliability/dependability*, with an *RII* of 0.938, is the top ranked competency in this category. The two second ranked competencies in this category are *teamwork* and *ethics*, each with an *RII* of 0.908.

C. Top ten ranked organizational Competencies

This section presents the top ten ranked functional and behavioral competencies shown in Tables 3.4 and 3.5, based on their *RII* values and irrespective of their competency category. Based on the ranking in Table 3.4, quality of work is the top ranked competency (*RII* = 0.969). The second top ranked competencies are technical/job knowledge and safety, health and environment, both with *RII* = 0.954. Commitment to safety (*RII* = 0.969) and cooperation and coordination (*RII* = 0.969) are ranked fourth and fifth respectively. The sixth ranked competencies include quality management, schedule management, scope management, and values and ethics, each with *RII* =

0.923. Construction technology/integration management and operations and maintenance are ranked tenth with RII = 0.908. Competencies from the technical and project management competency categories dominate the ten to-ranked competencies (Table 3.4), which reflects the priorities of organizations in the construction industry.

Table 3.4. Ten top-ranked functional competencies

No.	Competency	Competency category	*RII*	Overall rank
1	Quality of work	Technical	0.969	1
2	Technical/job knowledge	Technical	0.954	2
3	Safety, health, security and environment	Project management	0.954	2
4	Commitment to safety	Technical	0.938	4
5	Cooperation and coordination	Cross-functional	0.933	5
6	Quality management	Project management	0.923	6
7	Schedule/time management	Project management	0.923	6
8	Scope management	Project management	0.923	6
9	Values and ethics (integrity and respect)	Supervisory/managerial	0.923	6
10	Construction technology/ integration management	Production/operation	0.908	10
11	Operations and maintenance	Production/operation	0.908	10

Based on the rankings in Table 3.5, the first and second top ranked behavioral competencies are *leadership* (*RII* = 0.969) and *strategic thinking* (*RII* = 0.954), respectively. *Problem solving* and *reliability/dependability*, each with *RII* = 0.938, are ranked third, followed by *ability to build trust* (*RII* = 0.933) in fifth place. The sixth ranked competencies include *interpersonal skills* and *decision-making*, both with *RII* = 0.923. Competitiveness (*RII* = 0.917) is ranked eighth, followed by *adaptability/flexibility* and *achievement drive*, each with *RII* = 0.908 ranked ninth.

Table 3.5. Ten top-ranked behavioral competencies

No.	Competency	Competency category	RII	Overall rank
1	Leadership	Top management	0.969	1
2	Strategic thinking	Top management	0.954	2
3	Problem solving	First-line management	0.938	3
4	Reliability/dependability	Individual/personal	0.938	3
5	Ability to build trust	Organizational attributes	0.933	5
6	Interpersonal skills	Middle management	0.923	6
7	Decision-making	Middle management	0.923	6
8	Competitiveness	Organizational attributes	0.917	8
9	Adaptability/flexibility	Organizational attributes	0.908	9
10	Achievement drive	Organizational attributes	0.908	9

The proposed classification of organizational competencies, which was validated through the focus group, helps organizations to identify, classify, categorize, and prioritize their competencies based on their contexts (i.e., the size and type of organization as well as the construction industry sector in which they operate).

3.3.1.2 Organizational Performance Measures

The complete list of ranked organizational performance measures based on the focus group survey analysis is provided in Appendix B.3. Based on the rankings in Appendix B.3, among the ten top-ranked performance measures are, *Profitability* (*RII* = 0.967) is the top ranked performance measure. The second ranked performance measures include *return on investment*, *incident rate*, *time lost*, and *company image/reputation*, each with *RII* = 0.938. *Cash flow* (*RII* = 0.933) and *cost predictability* (*RII* = 0.933) are ranked sixth, followed by *return on capital* (*RII* = 0.923) and *safety performance* (*RII* = 0.917), ranked eighth and ninth, respectively. *Return on assets* and *competitive advantage* are the tenth most important performance measures, with *RII* = 0.908.

The top-ranked performance measures in their respective categories are as follows. *Cash flow* (*RII* = 0.933), *rework factor* (*RII* = 0.892), and *market returns* (*RII* = 0.800) are the top ranked performance measures in the KPI categories of cash flow, quality of work, and market share performance measures, respectively. *Revenue growth* (*RII* = 0.862), *net profit margin* (*RII* = 0.846), and *cost predictability* (*RII* = 0.933) are the top ranked performance measures in the KPO categories of growth, business efficiency, and effectiveness of planning, respectively. *Employee satisfaction* (*RII* = 0.908), *customer satisfaction* (*RII* = 0.877) and *company image/reputation* (*RII* = 0.938) were the top ranked performance measures in the PerM categories of internal customer satisfaction, external customer satisfaction, and competitiveness, respectively.

Quantitative analysis also enables the prioritization of organizational performance measures by ranking them based on their *RII* values in each category. For example, *market returns,* which shows an organization's sales as a percentage of an industry's total revenue over a fiscal year, is the top-ranked performance measure in the market share category. *Revenue growth*, which measures an organization's growth over time compared to the previous reporting period's performance, is the top-ranked performance measure in the growth category. *Company image/reputation*, which indicates how an organization is perceived by people when the organization's name is mentioned, is the top-ranked performance measure in the competitiveness category.

3.3.2 Focus Group Discussion Results

3.3.2.1 Categorization of Organizational Competency and Performance Measures

The majority of participants agreed that the categorization of both competency and performance measures is good, but one participant questioned the need for categorization. The moderators explained the rationale behind categorizing the long list of competency and performance measures in order to systematically group them to capture and depict the functional domains of a given organization (e.g., planning, design, construction etc.) in the construction industry. Categorization also helps the development of a technique for measuring and mapping competency to performance measures. A participant questioned why safety is included in some competency and performance categories given that it is an industry requirement. The majority of participants maintained that even if safety is a requirement, it is greatly important to evaluate it given the differences in implementation between organizations and between various construction industry sectors (i.e., safety requirements in the commercial construction sector are different than those in the heavy industrial construction sector). Two participants maintained that the behavioral competencies category is clearly defined, especially in terms of organizational attributes and managerial competencies. However, they argued that the items included under individual/personal competency category appear to be "characteristics" instead of competencies. The moderators cited past studies (e.g., IPMA 2015; Salajeghe et al. 2014; Takey and Carvalho 2015) to explain the basis for developing those individual competencies. In addition to individual cognitive abilities and traits, individual/personal competencies also include the knowledge, skill, ability (known as KSA) and experience that characterize a particular individual; hence, they are considered competencies. After a thorough discussion, the focus group reached consensus, agreeing that the categorization of organizational competency and performance measures is suitable and appropriate for use in construction organizations. Thus, the focus group validated the categorization of organizational competency and performance.

3.3.2.2 Gaps in Organizational Competency and Performance Measures

One of the issues participants highlighted is the overlap and repetition of competencies, such as *human resource management* and *resource management,* across different categories. The moderators explained that the competencies that are repeated in different categories have different levels of detail (e.g., they exist at the project and/or organizational level). It was also pointed out that some of the competencies (e.g., *human resources/personnel*) are at a higher (i.e., macro) level than some other competencies (e.g., *project human resource management*), which are at the micro level. The moderators explained that similar competencies in different categories were designed to capture organizational competency measures at different levels (e.g., project, business, and/or corporate levels). Such an approach is supported by the majority of participants.

A participant suggested that safety measures need to be grouped under KPOs instead of KPIs. The moderators explained that safety measures were grouped under KPIs because this categorization is supported by the literature, although some of the measures can also be considered KPOs. Another participant suggested that safety measures can be both KPIs and KPOs, stating, for instance, that the occurrence of a safety incident is an indicator that something serious might happen.

A participant raised the issue that some performance measures that are applicable to a certain organization type may not be appropriate for another organization type, such as owner versus contractor/service provider. For instance, performance measures that include return on assets and return on investment capture owners' perspectives. On the other hand, measures such as *market growth* and *sales growth* are more appropriate from the service perspective (i.e., for contractors and consultants). The moderators explained that the purpose of developing a comprehensive list of performance measures is to account for the context variables of organization type, organization size, and construction sector type, so that individual organizations can select the most appropriate performance measures.

3.3.2.3 Improvements Suggested by the Focus Group

These suggestions were also discussed during the focus group discussion. In order to address the presence of similar or repetitious competencies in different categories, participants recommended making more distinction between repeated competencies. The moderators explained that the competencies are distinguished by the definition of each individual competency and performance measure. Improvements to overall categorization and specific categories were suggested. Feedback from both the focus group survey and the discussion helped to capture practitioners' experiences in order to improve the list of competency and performance measures and their categorizations at an organizational level. The competency and performance measures that were recommended for inclusion or removal from the list were thoroughly analyzed, and those that were determined to exist and/or effectively capture competency or performance at the organizational level and that were supported by literature are included in order to meet the study objectives.

Competencies incorporated in the functional competency categories based on participants' feedback include: *interdisciplinary alignment* (general administration), *technical innovation* (technical), and *interface management* (cross-functional). Few competencies were suggested to be moved from their original category to a different category. *Delegation* is moved to the managerial/supervisory category from the cross-functional category, while *strategic planning and management* and *financial management* are taken out of the technical category and included under the cross-functional and project management categories, respectively.

Suggested additions to the list of performance measures include *revenue diversification* (cash flow), *near misses* (safety), and *work force growth* and *asset growth* (growth). *Cash flow* is moved to the financial stability category under KPIs based on focus group feedback. In addition, a new performance metric category, community relationships, which includes performance measures such as *equity*, *diversity*, *charitable institutions*, and *indigenous involvement* (aboriginal engagement targets), was suggested for addition. However, equity and diversity are elements of *manage and support diversity* under the general administration competency category, whereas charitable institutions and indigenous involvement needed to be added.

3.3.2.4 Suitability of Competency and Performance Measures for Collecting Data

Almost all participants agreed that the competency and performance measures provided were suitable for data collection. Furthermore, participants agreed that the presented approach mirrors most of their organizations' approaches to defining and measuring competency and performance. However, one participant felt strongly that measuring competency and performance is contingent on what the top management needs and also depends on where these priorities fit in the hierarchies of the organization. The moderators explained that the differences in organization type (i.e., owner, consultant, and contractor) and the construction sector in which these companies operate were taken into consideration when developing the categorization. For instance, site priorities include schedule and cost, while corporate priorities will include profit. Performance measures should be put on a spectrum that accounts for the perspective (i.e., owners, contractors, consultants, etc.) from which they are being considered. As a result, the competencies required by an owner organization may differ from those required by contractors or consultants. Therefore, the comprehensive list of organizational competency and performance measures was developed to help different types of organizations to select the appropriate competencies and performance measures based on the nature of their organization and the construction sector in which they operate.

3.3.2.5 Verified List of Organizational Competency and Performance Measures

All participants agreed that the list of competency and performance measures and their categories were appropriate for use in their respective organizations, thus verifying the list of competency and performance measures and validating their categorization. Based on quantitative and qualitative analyses of the focus group discussion, the final refined list of organizational competency and performance measures is presented in Tables 3.6 and 3.7, respectively.

In addition to competency and performance measures that were based on *RII* values, those recommended by the focus group were incorporated based on their relevance to the assessment of organizational-level competencies and based on supporting literature. Accordingly, the following competencies *i.e., interdisciplinary alignment* (Brassler and Dettmers 2017), *technical innovation* (Ozorhon et al. 2016), and *interface management* (Ahn et al. 2016) were included. In addition, performance measures such as *revenue diversification* (Sung et al. 2017), and *near misses* (Pereira et al. 2017) were included.

Table 3.6. Final list of organizational competencies

Group	Competency category	Competencies
Functional	General administration	Staff development/training; results orientation; goal orientation; human resources/personnel; interdisciplinary alignment*
	Technical	Quality of work; technical/job knowledge; commitment to safety; planning and organizing; technical innovation*
	Cross-functional	Cooperation and coordination (collaboration); strategic planning and management**; stakeholder focus; communications management; interface management*
	Production/operation	Construction technology/integration management; operations and maintenance; process engineering management; construction, production, and manufacturing; materials management
	Construction and engineering research and development	Business, legal, and public policy; construction law and regulation; information management systems/technology
	Project management competencies	Safety, health, security, and environment; quality management; schedule (time) management; scope management; change management; managing performance; cost management; commissioning and start-up; project monitoring and controlling; project resource management
	Supervisory/managerial	Values and ethics; engagement; management excellence; resource management; delegation***
Behavioral	Organizational attributes	Ability to build trust; competitiveness; adaptability/flexibility; achievement drive; innovation; organizational awareness, culture, and values
	Top management	Leadership; strategic thinking; judgement; analytical ability
	Middle management	Interpersonal skills; decision-making; consultation; negotiation; reasoning; conflict and crisis resolution/issue management
	First-line management	Problem-solving; integrity/high standards; planning and organizing; results orientation; responsiveness
	Individual/personal	Reliability/dependability; teamwork; ethics; initiative; commitment; effectiveness; self-regulation/control; motivation

* Incorporated based on focus group feedback, ** Moved from technical competency category, *** Moved from cross-functional competency category

Table 3.7. Final list of organizational performance measures

Metrics group	Category	Performance measures
KPIs	Quality of work	Rework factor; prevention, appraisal, and failure (PAF) model
	Market share	Market returns; market share
	Safety	Incident rate; time lost; safety performance; near misses*
	Financial stability	Cash flow; debt ratio; liquidity; revenue diversification*; credit availability*
KPOs	Profitability	Profitability; return on investment; return on capital; return on assets; net income; return on equity
	Growth	Revenue growth; sales growth; volume of works growth; workforce growth*; asset (equipment and facility) growth*
	Business efficiency	Net profit margin; efficiency ratio
	Effectiveness of planning	Cost predictability; time predictability; change cost factor
PerMs	Internal customer satisfaction	Employee satisfaction; employee turnover rate; average remuneration per employee
	External customer satisfaction	Customer satisfaction; customer retention/loyalty; percentage of repeat customers
	Competitiveness	Company image/reputation; competitive advantage; market advantage
	Community relationship*	Indigenous involvement; charitable institutions; local community project spending

*Incorporated based on focus group feedback

3.4 Chapter Summary

This chapter presents a review of competency and performance studies focusing on competency and performance measures at the organizational level in the construction industry. Common approaches to competency and performance identification and classification were explored. A focus group study was conducted to rank, verify and validate the list and categorization of organizational competency and performances measures, evaluate the importance of these measures in a given category based on their *RII* values and rankings, and refine the list of competency and performance measures. The list of competency and performance measures and validated their categorizations in that they can be used to collect data for measuring competency and performance at an organizational level.

The contributions of this chapter are threefold. First, this chapter presents a critical review of past studies and shows that competency studies at the organizational level for the construction domain are limited. This chapter contributes by addressing the gap in the research on organizational-level competency and performance studies specifically for the construction domain. Second, this chapter identifies, categorizes, and ranks a comprehensive list of organizational competency and performance measures. Third, the proposed competency and performance measure classification method was validated through a focus group, helping organizations in the construction industry to identify and categorize their competency and performance measures according to their context and construction industry sector. In the next chapter, a comparative analysis of organizational competencies influencing organizational performance as well as a correlation analysis to determine the relationship between competencies and organizational performance is presented.

3.5 References

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Chapter 4 Comparative Analysis of Organizational Competencies and Performance Influencing Performance

4.1 Introduction

The current economic situation is challenging, which creates a more competitive environment for organizations operating in the construction industry. Developing dynamic-capability in fast-changing environments such as construction is critical for organizations to ensure effective firm competitiveness and performance (Lin and Wu 2014). Competitive advantage exists while organizations outperform competitors and is gained through having superior organizational resources, capabilities, and competencies to provide competitive products or services (Aydiner 2019a). Some organizations are more successful than others in the process of resource accumulation and resource deployment to create distinct capabilities and/or competencies (Aydiner 2019b). Thus, these capabilities create a broader view of a firm by combining the resources and competencies in order to achieve superior performance (Aydiner 2019a).

Competency is the ability of an organization to perform activities, tasks, or processes that enable to achieve specified performance goals (Tiruneh and Fayek 2020). Past studies perceived organizational competencies as a multi-level construct at an individual, team/collective, and organizational level (Loufrani-Fedida and Missonier 2015). Accordingly, this chapter presents an illustrative analysis that uses surveys to identify the critical competencies influencing organizational performance and competencies with a higher potential for performance improvement according to senior management (SM), middle and lower-level management (MLM), as well as office and project site staff (OPS) respondents. Thus, this chapter has the following objectives: (1) identify critical competencies influencing performance; (2) identify competencies with a high potential for organizational performance improvement; (3) evaluate differences in respondent groups' perspectives; and (4) investigate relationship between organizational competencies and performance. In this chapter the critical competencies, as well as competencies with a high potential for improvement in organizational performance are evaluated based on survey responses from SM, MLM and OPS participants. Thus, incorporating construction practitioners' opinions through surveys ensures that critical parameters (e.g., competencies) influencing performance are identified for further analysis and modeling (Tsehayae and Fayek 2014).

The rest of this chapter is structured as follows. First, a review of past comparative analysis is presented. Second, the research methodology adopted in this chapter is discussed. Fourth, findings of the survey analysis is provided. Fifth, discussion on the findings of the survey analysis results is made. Finally, a summary of this chapter is provided.

4.2 Previous Comparative Analysis Studies

4.2.1 Comparative Analysis Studies on Respondent Perspectives

Comparative analysis of perspectives from different respondent groups is common in construction research. For instance, a study by Dai et al. (2009) and Tsehayae and Fayek (2014) conducted perspective analysis to compare the responses of project managers or foremen with the responses of tradespeople on factors affecting productivity. Raoufi and Fayek (2018) compared the perspectives of supervisors and craftspeople on factors influencing construction crew motivation and performance. Dai and Goodrum (2012) carried out perspective analysis to compare generational difference among Baby Boomers, Generation X, and Generation Y on craftworkers' perceptions on factors affecting labor productivity. Naoum et al. (2020) investigated the perceptions of women in construction consultancies, including project managers, architects, engineers, and surveyors, and compared them to men's perceptions in the same discipline and age groups. Zou and Zhang (2009) investigated and compared the perceptions of major safety risk factors in the Chinese and Australian construction industries. Although statistical significance test was not performed, the comparison of the top five construction safety risks showed that differences in perceptions between the chines and Australian construction industries (Zou and Zhang 2009).

4.2.2 Comparative Analysis in Competency Studies

Perspective analysis among different respondent groups help to gain a better understanding of differences among respondent groups (Dai and Goodrum 2012, Naoum et al. 2020, Wu and Issa 2013). It is important to determine instances where there is a lack of consensus on competencies among respondent groups to formulate effective improvement strategies, since competencies influencing organizational performance are multi-level. A higher level of agreement among the respondent groups will help in implementing improvement strategies while a lack of agreement will demand further investigation into the sources of difference before taking action (Dai et al. 2007, 2009; Dai and Goodrum 2012; Raoufi and Fayek 2018; Tsehayae and Fayek 2014). Thus, such analysis helps to compare perspectives on competencies influencing organizational performance as well as developing performance improvement strategies.

Comparative analysis studies related to competencies are few and limited to select aspects of competencies. For instance, a comparative analysis of stakeholder perceptions on BIM education/competencies was conducted, where the result showed agreement between academic and professional communities on the BIM competencies (Wu and Issa 2013). Likewise, Zou et al.

(2019) investigated the perceptions between architecture, engineering and construction (AEC) students and AEC industry professionals on BIM practices. Statistical tests using *t*-value and *F*-values were performed where the result showed there is no significant difference among the perceptions of the two respondent groups (Zou et al. 2019). A comparative analysis of participants' perceptions was conducted to evaluate the benefits, factors, challenges, or benefited parties in BIM implementation among Chinese practitioners (Jin et al. 2017a). Chong (2013) conducted a comparison of managerial competencies of Singaporean and British managers. The result showed similarity on eight out of 19 common competencies that suggests common values within different cultures (Chong 2013). On the other hand, the competency differences observed between British and Singaporean managers are the result of differences in private and public sector work environments (Chong 2013). The comparative analysis in the above competency studies are based on a single evaluation scale and descriptive statistics (i.e., mean score or *RII*). Furthermore, most of the studies carry out the analysis using respondent groups rankings which is not indicative of the statistical significance of the agreement and/or difference. Thus, this chapter provides a methodological approach for a comprehensive analysis of critical competencies influencing performance and competencies with a high potential for performance improvement.

4.3 Research Methodology

4.3.1 Identify Organizational Competencies and Performance Metrics Through Literature Review

A systematic literature review and detailed content analysis was conducted to identify organizational competencies and performance metrics in construction as discussed in Chapter 3. As a result, a total of 101 competencies (i.e., 58 functional and 43 behavioral competencies) were selected and grouped under 12 categories. Furthermore, a total of 44 organizational performance metrics and classified them as KPIs) KPOs, and PerMs. Performance metrics can be either leading indicators (e.g., KPIs), lagging indicators (e.g., KPOs), or both (e.g., PerMs).

4.3.2 Verify List of Organizational Competencies and Performance Metrics Through Focus Group

A focus group was conducted to verify and validate the list and categorization of organizational competencies influencing organizational performance as well as performance metrics. Experts participating in the focus group reviewed the list and proposed additional organizational competencies and performance metrics they thought important at an organization level. The initial list of organizational competencies was then updated to incorporate feedback from the focus group and include proposed additional competencies that are backed by the literature. The focus group allowed for the development of a comprehensive list of organizational competencies and performance metrics that not only considers the literature in construction and non-construction domains, but also captures the opinions of construction experts practicing in the industry. More details about the focus group results can be found in Tiruneh and Fayek (2020).

4.3.3 Prepare Data Collection Forms

In this stage, data collection forms were prepared, and pilot tested prior to data collection. Data collection forms were developed using the finalized list of organizational competencies and performance metrics based on the focus group results. Furthermore, the list of organizational competencies and performance metrics were pilot tested with a construction company prior to data collection to ensure that respondents understood the data collection forms as well as to check applicability of the evaluation, assessment, and measurement scales and techniques of the data collection forms in construction organizations. Final data collection forms were then developed incorporating feedback from the pilot survey. Tables 4.1 and 4.2 presents the updated list and categorization of organizational competencies and performance metrics used to develop the surveys. Moreover, a definition of organizational competencies and performance metrics is provided to help respondents understand the meaning of each competency and performance metric while completing the surveys. Appendix C provides the complete list and definition of each competency and performance metrics in the data collection forms. Two surveys – the SM survey and the staff survey – were developed to collect organizational competencies influencing organizational performance. The SM survey addressed a total of 85 competencies (48 functional and 37 behavioral competencies). The staff survey consisted of 63 competencies (34 functional and 29 behavioral competencies). The SM survey addresses everything in the staff survey plus additional organizational competencies and performance metrics that can only be evaluated by SM and were not known to the other respondent group. Appendix D depicts sample data collection forms.

The first section of the data collection forms addresses respondents' background information, which includes demographic information, respondent position, years of experience, and respondents' general opinion regarding the company's organizational competency and performance in general. Appendix D.1 shows a sample data collection form for background information. The second section addresses organizational functional competencies evaluated based on their maturity (i.e., the extent to which a specific competency exists in the organization) and impact on performance (i.e., the level of impact of a specific competency on overall performance of the organization). Maturity of functional competencies is measured on a scale ranging from 1 ("Informal") to 5 ("Optimized") (Crawford 2015; Willis and Rankin 2012). A seven-point Likert

Table 4.1. Final list of organizational competencies for data collection

Group	Competency category	No. of competencies	Competencies
Functional	General administration	5	Staff development/training; human resources/personnel management; goal orientation; management and support of diversity; interdisciplinary alignment
	Technical	8	Quality of work; technical/job knowledge; commitment to safety; planning and organizing of tasks/activities; technical innovation; business acumen/business management skills; market management; finance management
	Cross-functional	6	Cooperation and coordination (collaboration); strategic planning and management; customer/stakeholder focus; communications management; interface management; digitalization implementation
	Production/operation	6	Construction technology/integration management; operations and maintenance; process engineering and management; construction, production, and manufacturing; product engineering; materials management
	Construction and engineering research and development	4	Business, legal, and public policy; construction law and regulation; management information systems/technology; new technology/product development
	Project management	15	Quality management; health and safety management; schedule (time) management; scope management; change management; managing performance; cost management; commissioning and start-up; risk management; design development; integration management; contract administration; procurement management; commitment to sustainability
	Supervisory/managerial	4	Engagement; management effectiveness/excellence; delegation; resource management
	Subtotal	**48**	
Behavioral	Organizational attributes	6	Ability to build trust; competitiveness; adaptability/flexibility; achievement drive; innovation; organizational awareness
	Top management	5	Leadership; strategic thinking; judgement; Analytical ability/thinking, values and ethics
	Middle management	7	Interpersonal skills; decision-making; consultation; negotiation; reasoning; Conflict and crisis resolution/issue management; assertiveness
	First-line management	7	Problem-solving; integrity/high standards; results orientation; responsiveness; influence; communication; incisiveness
	Individual/personal	12	Reliability/dependability; teamwork; ethics; initiative; commitment; effectiveness; self-regulation/control; motivation; resourcefulness; perseverance; attention to detail; professionalism
	Subtotal	**37**	
	Total	**85**	

Table 4.2. Organizational performance categories and number of metrics

Level	Organizational performance metrics category	Organizational performance metrics subcategory	Number of metrics	Metrics
Organizational/operational	KPIs	Market performance	2	Market share, market returns
		Financial stability	2	Cash flow; revenue diversification
	KPOs	Profitability ratio	4	Profitability; net income; return on sales; hanging invoice
		Growth	4	Revenues growth; sales growth; volume of works growth rate; work force growth
		Business efficiency	2	Efficiency ratio; net profit margin
	PerMs	Employee satisfaction	5	Employees' satisfaction; remuneration; employee turnover rate; compensation and benefits; merit increase; social services
		Customer satisfaction	4	Customer satisfaction; customer retention/loyalty; percentage of repeat customers; number of complaints
		Competitiveness	3	Company image/reputation; competitive advantage; market advantage
Project	KPIs	Quality of work	2	Rework factor; prevention, appraisal and failure (PAF) model
		Safety	9	Incidents rate; safety performance; accident frequency rate; near misses; behavior-based observation (BBO) rate; total injury rate; project total recordable incident frequency (PTRIF); severity; total incidents rate (non-medical)
	KPOs	Effectiveness of planning	5	Cost predictability; time predictability; change cost factor; cost growth/increase; time/schedule growth/increase
Total			**42**	

scale was adopted to evaluate impact on performance ranging from 1 (“Extremely low”) to 7 (“Extremely high”) (CII 2006; Dai and Goodrum 2012; Dai et al. 2009; Tsehayae and Fayek 2014). Appendix D.2 shows a sample data collection form for functional competencies. The third section covers behavioral competencies evaluated based on agreement (i.e., the extent to which the respondent agrees that a specific competency exists in the organization) and impact on performance. As proposed by CII (2006), Dai and Goodrum (2012), Dai et al. (2009), and Tsehayae and Fayek (2014) a seven-point Likert scale was adopted to evaluate agreement and impact. Agreement is measured on a scale ranging from 1 (“Strongly disagree”) to 7 (“Strongly agree”). Appendix D.3 shows a sample data collection form for behavioral competencies. The fourth section addresses subjective evaluation of organizational performance metrics based on the respondent’s opinion. Performance metrics related to PerMs were evaluated using a satisfaction scale ranging from 1 (“extremely unsatisfied”) to 5 (“extremely satisfied”). Subjective performance metrics related to KPIs and KPOs are evaluated using a scale ranging from 1 (“very low”) to 5 (“very high”). Appendix D.4 shows a sample data collection form for subjective performance metrics.

Each of the categories of organizational performance have several metrics (Table 4.2). A total of 11 different organizational performance metrics categories were identified, which consist of 42 performance metrics (Tiruneh and Fayek 2020). Table 4.2 lists the number of performance metrics in each category used for data collection. Appendix C.3 presents a detailed list of the different organizational performance metrics, their definitions, and formulae.

Performance metrics related to KPIs and KPOs are collected at the organizational (operational) level and project level. Performance data for KPI and KPO metrics are extracted from relevant actual organizational/project documents. For performance metrics related to PerMs, evaluation forms were distributed to SM, MLM, and OPS respondent groups.

4.3.4 Determination of Sample Size

The surveys were designed to be administered in any construction company (e.g., industrial, commercial, and institutional). The population (i.e., the number of workers in a given project or department) for the surveys was assumed to be made up of all construction personnel in the construction company (and/or projects) under study. This population composition ensures that the critical competencies identified through the surveys are applicable to the company's context and its project work force.

Determination of sample size (i.e., the number of respondents to be surveyed from the population of workers) is essential to ensure the reliability and accuracy of results. Since the surveys address competencies from individual level up to an organizational level (i.e., multi-level at individual, project, and organization levels), respondents representing different levels of the participating company and its project sites were asked to participate in the study (Dai and Goodrum 2012; Dai et al. 2009; El-Gohary and Aziz 2014; Jarkas and Radosavljevic 2013; Robinson 2014). Accordingly, the survey population was stratified based on the list of employees provided by the participating construction company into the following levels: SM, MLM, and OPS (i.e., staff working at head/regional office and project sites). Once the population for each stratum is established, random sampling is done. Stratified random sampling is an appropriate method in this situation, as the structure within the population of each stratum is assumed to be similar in terms of role and function. Random sampling also ensures that respondents have an equal chance of being selected, which helps to prevent biased selection based on convenience (Robinson 2014).

The construction company had 14 SM, 28 MLM and 90 OPS (i.e., a total population of 132 people). Among a survey population of 132 in the participating company, a total of 68 respondents were required in order to achieve a 90% confidence interval with a 10% margin of error.

4.3.5 Collect Organizational Competencies and Performance Metrics Data

Data collection for organizational competencies was performed with a construction company actively involved in industrial projects, via an online survey through Survey Monkey with the company's office and project personnel, including senior management, project managers, field supervisors, and foremen. Actual company performance metrics data related to KPIs and KPOs were collected at the organizational level (operational) and project level. Thus, performance data for KPIs and KPOs were extracted from relevant actual organizational/project documents. For performance metrics related to subjective performance metrics such as PerMs, evaluation forms were distributed to SM, MLM, and OPS.

Participants holding SM positions (e.g., VPs, GMs, Directors/Managers of departments, etc.) completed the SM survey, while all other participants completed the staff survey. Of the 132 surveys distributed, 80 participants returned the survey. From 14 SM, 11 responded to the SM survey. Likewise, from 28 MLM, 21 responded and from 90 OPS, 48 responded to the staff survey. The target of this study was to achieve a 10% margin of error and 90% confidence interval. Among a survey population of 132 in the participating company, a total of 68 respondents were required in order to achieve a 90% confidence interval with a 10% margin of error. The required 90% confidence level was achieved because 80 respondents returned the survey, which provides 92% confidence interval with 10% margin of error. All collected surveys were then anonymized using a code sheet.

4.3.6 Data Analysis

The data analysis approach presented in this section is used to determine the critical competencies influencing organizational performance and to identify the competencies with a high potential for organizational performance improvement. A comparative analysis of SM and staff survey results was performed to reveal the differences in perspectives between each group. Statistical tests, including t-tests and F-tests, were performed to determine if there was a statistically significant difference between the mean and variance of the evaluations among the respondent groups. Furthermore, a correlation analysis was also performed to assess the relationship between organizational competencies and organizational performance.

The analysis approach and calculations shown in the following two sub-sections are used to determine the evaluation scores and ranks for each competency in the survey (Dai and Goodrum 2012; Dai et al. 2009; Raoufi and Fayek 2018; Tsehayae and Fayek 2014). The analysis used in this section follows the approach by Raoufi and Fayek (2018) with some differences in formulation. These differences originate from the fact that in Raoufi and Fayek (2018), evaluation scores were based on agreement-importance, whereas this chapter bases evaluation scores on maturity/agreement-impact. The data analysis steps are discussed as follows.

4.3.6.1 Analysis for Identifying Critical Competencies Influencing Performance

Survey responses were combined to calculate evaluation scores based on the maturity/agreement and impact of each competency. The evaluation scores were then normalized based on the maximum evaluation score, and the competencies were ranked accordingly. The critical competencies influencing organizational performance are the ones that have high evaluation scores, i.e., competencies with high maturity/agreement and high impact. The rankings for the competency categories were based on the average evaluation scores of competencies in each category. The average evaluation scores were then normalized based on the maximum average evaluation score, and the competency categories were ranked accordingly. However, the category evaluation scores, and the ranking will also depend on the number of competencies within the competency category. As shown in Table 4.1, the number of competencies per category varies, and therefore the category evaluation scores will be skewed towards categories with fewer competencies where any of the competencies have a high evaluation score. All competencies are analyzed using the calculations presented in Equations (4.1) to (4.7) below in order to identify critical competencies influencing organizational performance.

The functional competencies are evaluated using maturity-impact scales as shown in Equation (4.1) through Equation (4.4). First, the weighted percentage of maturity *(R_M)* for a given functional competency is computed using Equation (4.1), where the maximum possible weighted percentage of maturity equals 33.33.

$$R_M = \frac{(A*1+B*2+C*3+D*4+E*5)}{(1+2+3+4+5)} * 100 \tag{4.1}$$

where A, B, C, D, and E = percentage of respondents rating the maturity of the competency as 1 ("informal") to 5 ("optimized"), respectively.

Next, the weighted percentage of impact *(R_I)* of a given functional competency is computed using Eq. (4.2), where the maximum possible weighted percentage of impact equals 25.

$$R_I = \frac{(T*1+U*2+V*3+W*4+X*5+Y*6+Z*7)}{(1+2+3+4+5+6+7)} * 100 \tag{4.2}$$

where T, U, V, W, X, Y, and Z = percentage of respondents rating the impact of the competency as 1 ("extremely low") to 7 ("extremely high"), respectively.

Finally, the evaluation index and evaluation scores for each competency is computed using Equation (4.3) and Equation (4.4). The evaluation index is the product of the weighted percentage of maturity *(R_M)* and the weighted percentage of impact *(R_I)*. The evaluation score is computed by dividing the evaluation index of a given competency by the maximum possible evaluation score, which equals 833.33. The maximum possible evaluation score is the product of the maximum values of weighted percentage of maturity (=33.33) and impact (=25).

$$Evaluation\ Index_{MI} = R_M * R_I \tag{4.3}$$

$$Evaluation\ Score_{MI} = \frac{Evaluation\ Index_{MI}}{833.33} * 100 \tag{4.4}$$

The behavioral competencies are evaluated using agreement-impact scales as depicted in Equation (4.5) to Equation (4.7). The weighted percentage of agreement *(R_A)* for a given competency is computed using Equation (4.5), where the maximum possible weighted percentage of agreement equals 25. The weighted percentage of impact *(R_I)* of a given behavioral competency is determined using Equation (4.2), where the maximum possible weighted percentage of impact equals 25.

$$R_A = \frac{(F*1+G*2+H*3+I*4+J*5+K*6+L*7)}{(1+2+3+4+5+6+7)} * 100 \tag{4.5}$$

where F, G, H, I, J, K, and L = percentage of respondents rating the agreement with the existence of the factor in the project from 1 (“strongly disagree”) to 7 (“strongly agree”), respectively.

The evaluation index and evaluation scores for each behavioral competency is computed using Equations (4.6) and (4.7). The evaluation index is the product of the weighted percentage of agreement *(R_A)* and the weighted percentage of impact *(R_I)*. The evaluation score is computed by dividing the evaluation index of a given competency by the maximum possible evaluation score, which equals 625. The maximum possible evaluation score is the product of the maximum values of weighted percentage of maturity (=25) and impact (=25).

$$Evaluation\ Index_{AI} = R_A * R_I \tag{4.6}$$

$$Evaluation\ Score_{AI} = \frac{Evaluation\ Index_{AI}}{625} * 100 \tag{4.7}$$

4.3.6.2 Analysis for Identifying Potential Competencies for Performance Improvement

The competencies influencing performance are the ones that showed high maturity/agreement and high impact. These competencies are important targets for improvement, or if they are already fully satisfied, it is vital to make efforts to keep them at their highest possible maturity/agreement level. However, it should be noted that improving a competency that is already close to its highest possible maturity/agreement level is very difficult and is sometimes not feasible (Raoufi and Fayek 2018). In such cases, there is simply no space for the improvement of a competency because it is already close to perfect or desired condition. Therefore, the competencies with the highest potential improvement in terms of their effect on organizational performance are those competencies that simultaneously exhibit the lowest levels of maturity/agreement and the highest levels of impact on performance. It is critical to identify these competencies and find ways to enhance them in order to achieve performance improvement. Potential competencies for performance improvement were analyzed in terms of their potential improvement score calculated based on the procedures described in Equations (4.8) to (4.13). If those competencies are enhanced, they have the highest potential to improve organizational performance. The potential improvement scores were normalized based on the maximum score, and the potential competencies for performance improvement were ranked accordingly. The rankings for the categories of potential competencies for performance improvement are based on the average potential improvement scores of competencies in each category.

The potential improvement functional competencies are evaluated as shown in Equations (4.8) to (4.10). First, the weighted percentage of immaturity *(R_{Im})* for a given functional competency is computed using Equation (4.8), where the maximum possible weighted percentage of immaturity equals 33.33.

$$R_{Im} = \frac{(A*5+B*4+C*3+D*2+E*1)}{(1+2+3+4+5)} * 100 \quad (4.8)$$

where A, B, C, D, and E = percentage of respondents rating the agreement with the maturity of the competency as 1 (“informal”) to 5 (“optimized”), respectively.

Next, the weighted percentage of impact *(R_I)* of a given functional competency is computed using Equation (4.2), where the maximum possible weighted percentage of impact equals 25. Then, the potential improvement index for each competency is computed using Equation (4.9). The potential improvement index is the product of the weighted percentage of immaturity *(R_{Im})* and the weighted percentage of impact *(R_I)*.

$$Potential\ Improvement\ Index_{ImI} = R_{Im} * R_I \quad (4.9)$$

Finally, potential improvement scores for each competency are calculated using Equation (4.10). The potential improvement scores is computed by dividing the potential improvement index of a given competency by the maximum possible potential improvement score, which equals 833.33. The maximum possible potential improvement score is the product of the maximum values of weighted percentage of immaturity (=33.33) and impact (=25).

$$Potential\ Improvement\ Score_{ImI} = \frac{Potential\ Improvement\ Index_{ImI}}{833.33} * 100 \quad (4.10)$$

The potential improvement behavioral competencies are evaluated using disagreement-impact scales as shown in Equations (4.11) to (4.13). First, the weighted percentage of disagreement *(R_D)*

for a given competency is computed using Equation (4.11), where the maximum possible weighted percentage of agreement equals 25.

$$R_D = \frac{(F*7+G*6+H*5+I*4+J*3+K*2+L*1)}{(1+2+3+4+5+6+7)} * 100 \qquad (4.11)$$

where F, G, H, I, J, K, and L = percentage of respondents rating the agreement with the existence of the factor in the project from 1 ("strongly disagree") to 7 ("strongly agree"), respectively.

Next, the weighted percentage of impact *(R_I)* of a given behavioral competency is determined using Equation (4.2), where the maximum possible weighted percentage of impact equals 25. Then, the potential improvement index for each behavioral competency is computed using Equation (4.12). The evaluation index is the product of the weighted percentage of disagreement *(R_D)* and the weighted percentage of impact *(R_I)*.

$$Potential\ Improvement\ Index_{DI} = R_D * R_I \qquad 4.(12)$$

Finally, potential improvement scores for each competency are calculated using Equation (4.13). The potential improvement score is computed by dividing the potential improvement index of a given competency by the maximum possible potential improvement score, which equals 625. The maximum possible potential improvement score is the product of the maximum values of weighted percentage of maturity (=25) and impact (=25).

$$Potential\ Improvement\ Score_{DI} = \frac{Potential\ Improvement\ Index_{DI}}{625} * 100 \qquad (4.13)$$

4.3.6.3 Comparative Analysis of Respondents' Perspectives

The difference of perspectives among the respondent groups was investigated based on the ranking of each respondent groups. In addition, statistical tests were performed to investigate if there is a statistically significant difference between each group's perspectives regarding critical competencies influencing performance. Statistical significance tests of perception differences among different respondent groups have been previously applied in construction research. Subgroup analysis using parametric methods such as analysis of variance (ANOVA) and the two-sample t-test were commonly used for surveys divided into subgroups (Aksorn and Hadikusumo 2008; Jin et al. 2017a, b; Xu et al. 2018; Zou et al. 2019). The robustness of parametric methods was demonstrated in data samples that were either small or not normally distributed (Xu et al. 2018). The two-sample t-test was adopted to test the mean values for consistencies among respondent groups' perceptions. In this chapter, the *t*-test and *F*-test were conducted using SPSS version 24 software to compare group means to evaluate differences in their perspectives. The significance of the differences based on the *t*-test and *F*-test based on the null hypothesis that there is no perception difference among the groups, will be rejected for *p*-value (significance level) lower than 0.05 (i.e., 95% confidence level).

4.3.6.4 Correlation Analysis to Determine Relationship Between Competency and Performance

Pearson correlation analysis is performed to investigate the relationships between organizational competencies and organizational performance. Pearson correlation analysis was chosen since it is the most common technique for correlation analysis (Bobko 2001, Hair et al. 2018). Pearson correlation analysis applies Equations (4.14) and (4.15), shown below, to measure the degree of linear relationship between a pair of variables (Fellows and Liu 2015; Kline 2013; Lee et al. 2000).

$$\sigma_{X,Y} = \sum_{j=1}^{m} \sum_{i=1}^{n} (X_i - \mu_X)(Y_j - \mu_Y)\, P(X_i, Y_j) \tag{4.14}$$

where $\sigma_{X,Y}$ stands for the covariance of the two variables (X,Y), X_i stands for the value of X in the observation number i, and μ_X represents the mean value of the X values. Similarly, Y_i stands for the value of Y in the observation number j, and μ_Y represents the mean value of the Y values. Additionally, $P(X_i, Y_j)$ represents the probability of occurrence of (X_i, Y_j). The Pearson correlation coefficient for the two sets of data X and Y can be calculated using Equation (4.15).

$$\rho = \frac{\sigma_{X,Y}}{\sigma_X \sigma_Y} \tag{4.15}$$

where ρ stands for the Pearson correlation coefficient, σ_X stands for the standard deviation of X, and σ_Y stands for the standard deviation of Y.

The Pearson correlation coefficient is used to determine the direction and magnitude of the relationships between a pair of variables. The direction of the relationship between two sets of variables can be positive or negative (Hair et al. 2018). A positive relationship shows that the two variables change in the same direction (i.e., simultaneously increasing or simultaneously decreasing), while a negative relationship shows that the two variables change in opposite directions (i.e., if one variable increases the other variable will decrease).

The magnitude of the relationship between the two variables is determined by the value of the Pearson correlation coefficient. The Pearson correlation coefficient varies between –1 and 1; a value of –1 shows a perfect negative relationship, while a coefficient of 1 shows a perfect positive relationship. Moreover, a Pearson correlation coefficient of zero shows that the correlation analysis cannot confirm the existence of any relationship between the two variables. Based on the value of the Pearson correlation coefficient, the magnitude of the relationship between a pair of variables may fall into one of the three categories presented in Table 4.3, which were originally introduced by Cohen (1988). Bajpai (2017) used similar categories to determine the magnitude of relationships between two variables.

Table 4.3. Categories of the Pearson correlation coefficient ($\boldsymbol{\rho}$) magnitude

Pearson correlation coefficient value	Magnitude of the relationship
$0.1 \leq \lvert\rho\rvert < 0.3$	Weak correlation
$0.3 \leq \lvert\rho\rvert < 0.5$	Moderate correlation
$0.5 \leq \lvert\rho\rvert$	Strong correlation

4.4 Findings of Organizational Competencies Influencing Performance

4.4.1 Data Reliability and Validity

The reliability and validity of the survey were checked by examining the consistency with which different items express the same concept (De-Vaus 2001). Cronbach (1951) developed Cronbach's alpha, to measure the average correlation or internal consistency amongst the survey and estimates the reliability of a questionnaire set (Jin et al. 2017b; Tsehayae and Fayek 2014; Xu et al. 2018). Cronbach's alpha was used to examine the internal consistency or reliability of the SM and staff surveys. Equations (4.4) and (4.7) indicate that the evaluation scores are based on weighted percentages of all responses. Since the survey statistical values require individual response values, it is not possible to use the evaluation scores to measure the different competency survey statistical values. Thus, the use of the impact rating for each competency is appropriate for such survey designs (Dai and Goodrum 2012; Dai et al. 2009; Tsehayae and Fayek 2014). The impact rating responses of the 85 competencies included in the SM survey and 62 competencies included in the staff survey were extracted from the surveys collected. Then, using SPSS version 24 software, the Cronbach's alpha statistical values for the SM and staff surveys for the three respondent groups were determined. As the Cronbach's alpha closer to 1.0, the greater the internal consistency of the data collected among the different respondents. George and Mallery (2003) indicated that a Cronbach's alpha of 0.7 or greater is considered acceptable internal consistency. The Cronbach's alpha used to analyze the consistency of the SM, MLM, and OPS had a value of 0.980, 0.958 and 0.989, respectively. Although all sets of evaluation showed excellent consistency, it is evident that the evaluation of the OPS have the highest internal consistency compared to the SM and MLM evaluations. Next, the survey results in terms of competency category rankings and top 10 critical competencies influencing performance for each respondent group are presented. Furthermore, an investigation into the differences in perspective on critical competencies is also presented.

4.4.2 Comparative Analysis Based on Ranking of SM and Staff Survey Results

In this section, the perspectives of the SM, MLM, and OPS are compared based on the ranking of competencies that are common to both SM and staff survey. In all, 32 common functional competencies in 6 categories and 28 behavioral competencies in 5 categories were evaluated between the SM survey and the staff survey. Rankings for the common competencies were derived from the evaluation scores assigned by each respondent group. The evaluation scores were then normalized, based on the maximum score in the range of 0 to 1, and the competencies were ranked accordingly. The rankings for the common competency categories are based on the average evaluation scores of competencies in each category.

4.4.2.1 Competency Category Ranking

The rankings of the competency categories, according to their average evaluation scores are shown in Table 4.4. These rankings are based on the average evaluation scores of competencies in each category. The result showed that individual/personal competency category appeared in the top three ranked categories for all respondent groups.

Table 4.4. Ranking and evaluation scores of critical competency categories influencing performance

Competency category	SM survey	Staff survey	
	SM	MLM	OPS
Functional competency			
General administration	5(0.661)	6(0.721)	6(0.815)
Technical	**2(0.927)**	**1(1.000)**	**1(1.000)**
Cross-functional	4(0.732)	**3(0.807)**	**3(0.917)**
Production/operations	6(0.635)	5(0.732)	5(0.855)
Project management	**1(1.000)**	**2(0.932)**	**2(0.984)**
Supervisory/managerial	**3(0.835)**	4(0.739)	4(0.868)
Behavioral competency			
Organizational attributes	5(0.759)	5(0.767)	5(0.854)
Top management	4(0.872)	**2(0.856)**	**1(1.000)**
Middle management	**2(0.962)**	4(0.845)	**2(0.999)**
First line management	**3(0.904)**	**3(0.837)**	4(0.940)
Individual/personal	**1(1.000)**	**1(1.000)**	**3(0.941)**

Note: The values in brackets indicate the normalized evaluation score of each category; values in bold represent the top three categories.

Differences in perspectives among the SM survey and staff survey (MLP and OPS) respondents regarding the critical competency categories influencing performance were analyzed. The results show strong agreement by the respondent groups on critical competency categories common to both SM and staff surveys. Of the top three critical functional competency categories identified by the SM respondents, two were included in the top three critical competency categories identified by both MLM and OPS respondents: "project management" and "technical" competency categories. Of the top three critical behavioral competency categories identified by the SM respondents, two were included in the top three critical competency categories identified by both MLM and OPS respondents: "individual/personal" and "top management" competency categories. The three respondent groups have similar views on critical competency categories influencing organizational performance. Even though they have different evaluation score values, the top three ranked functional and competency categories identified by both MLM and OPS respondents were found to be similar. Thus, MLP and OPS respondent groups have very similar views on critical competency categories influencing organizational performance.

4.4.2.2 Critical Competencies Influencing Organizational Performance

Table 4.5 presents the top 10 critical competencies influencing performance as ranked by the SM survey and staff survey respondents. Of the top 10 critical functional competencies identified by SM respondents, seven and six competencies were included in the top 10 critical competencies identified by MLM and OPS respondents, respectively. The five critical functional competencies included in the top 10 critical competencies based on the SM, MLM, and OPS respondents include "commitment to safety", "quality of work", "project health and safety management", "customer/stakeholder focus" and "project scope management". In the same manner, of the top 10 critical behavioral competencies identified by SM respondents, seven were included in the top 10 critical competencies identified by MLM and OPS respondents. The five critical behavioral competencies included in the top 10 critical competencies in the SM, MLM, and OPS respondents include "motivation", "professionalism", "responsiveness" and "values and ethics". Thus, SM and MLM respondent groups have highly similar views regarding critical functional and behavioral competencies that influence organizational performance. SM and OPS respondent groups have highly similar views regarding critical behavioral competencies while they revealed similar views regarding critical functional competencies that influence organizational performance. However, the MLM and OPS respondent groups have somewhat similar views regarding critical competencies that influence organizational performance.

Table 4.5 Top 10 critical competencies influencing performance common in SM and staff survey

Rank	Competency	SM survey	Competency	Staff survey		
		SM Evaluation score		MLM Evaluation score	Competency	OPS Evaluation score
	Functional					
1	Commitment to safety	1.000	Commitment to safety	1.000	Commitment to safety	1.000
2	Quality of work	0.858	Quality of work	0.881	Project health safety management	0.938
3	Project cost management	0.843	Project health safety management	0.838	Quality of work	0.833
4	Project health safety management	0.836	Customer/stakeholder focus	0.835	Management and support of diversity	0.808
5	Project change management	0.820	Project quality management	0.769	Technical/job knowledge	0.801
6	Customer/stakeholder focus	0.809	Technical/job knowledge	0.755	Communications management	0.787
7	Project scope management	0.786	Project finance management	0.693	Customer/stakeholder focus	0.769
8	Project schedule (time) management	0.766	Project scope management	0.682	Project scope management	0.755
9	Management effectiveness/excellence	0.723	Project cost management	0.670	Project schedule (time) management	0.752
10	Resource management	0.714	Project change management	0.640	Product engineering	0.713
	Behavioral					
1	Motivation/commitment	1.000	Teamwork	1.000	Values and ethics	1.000
2	Reasoning	0.983	Professionalism/ethics	0.893	Decision making	0.978
3	Influence	0.904	Attention to detail	0.853	Judgment	0.967
4	Attention to detail	0.900	Problem solving	0.849	Responsiveness	0.961
5	Professionalism/ethics	0.898	Values and ethics	0.834	Analytical ability/thinking	0.950
6	Interpersonal skills	0.881	Motivation/Commitment	0.834	Interpersonal skills	0.950

Rank	Competency	SM survey SM Evaluation score	Competency	Staff survey MLM Evaluation score	Competency	OPS Evaluation score
7	Decision making	0.869	Reliability/dependability	0.821	Conflict and crisis resolution / issue management	0.944
8	Responsiveness	0.858	Conflict and crisis resolution / issue management	0.802	Ethics/professionalism	0.904
9	Teamwork	0.854	Responsiveness	0.786	Motivation/commitment	0.904
10	Values and ethics	0.849	Effectiveness	0.780	Leadership	0.900

4.4.2.3 Competencies with a High Potential for Organizational Performance Improvement

Table 4.6 presents the top 10 competencies with a high potential for improvement in organizational performance, as ranked by the SM survey and staff survey respondents. The functional competencies listed in Table 4.6 are the ones that have both a low level of maturity and a high level of impact on performance. Increasing the maturity of these competencies will improve the performance of the organization (and/or its projects) since those competencies demonstrate high levels of impact. Therefore, identifying the competencies with a high potential for improvement in performance will provide companies with insight into competencies that may possibly affect performance on future organizational operations and projects.

The behavioral competencies listed in Table 4.6 are the ones that have both a low level of agreement and a high level of impact. For such competencies, if the agreement levels are increased (i.e., if respondents display a high level of agreement regarding the existence of these competencies across the organization and its project), because those competencies demonstrate high levels of impact, the organizational performance will be improved. The perspectives of the SM survey respondents and the staff survey respondents (Table 4.6) were very close in terms of the potential competencies for organizational performance improvement. Of the top 10 potential functional competencies identified by SM respondents, three and five competencies appeared in the top ten potential functional competencies identified by the MLM and OPS respondents, respectively. The three competencies included in the top 10 potential functional competencies based on the SM, MLM, and OPS respondents include “project procurement management”, “resource management” and “interdisciplinary alignment”. In the same manner, of the top 10 potential behavioral competencies identified by SM respondents, five and two competencies appeared in the top ten

Table 4.6 Top 10 potential competencies for performance improvement common in SM and staff survey

		SM survey		Staff survey		
Rank	Competency	SM Potential improvement score	Competency	MLM Potential improvement score	Competency	OPS Potential improvement score
	Functional					
1	Project procurement management	1.000	Materials management	1.000	Management effectiveness/excellence	1.000
2	Resource management	0.892	Project procurement management	0.970	Project change management	0.982
3	Interdisciplinary alignment	0.885	Planning and organizing of tasks/activities	0.939	Materials management	0.980
4	Interface management	0.879	Resource management	0.907	Resource management	0.978
5	Management effectiveness/excellence	0.850	Project schedule (time) management	0.901	Project procurement management	0.977
6	Project integration management	0.847	Human resource (personnel) management	0.889	Human resource (personnel) management	0.971
7	Project cost management	0.842	Interdisciplinary alignment	0.889	Project cost management	0.963
8	Goal orientation	0.841	Project change management	0.878	Interdisciplinary alignment	0.960
9	Communications management	0.841	Delegation	0.878	Project schedule (time) management	0.955
10	Engagement	0.841	Project risk management	0.876	Delegation	0.948
	Behavioral					
1	Leadership	1.000	Results orientation	1.000	Attention to detail	1.000
2	Innovation	0.916	Innovation	0.976	Teamwork	0.979
3	Strategic thinking	0.905	Conflict and crisis resolution / issue management	0.974	Adaptability/flexibility	0.957
4	Results orientation	0.861	Leadership	0.968	Resourcefulness/initiative	0.953
5	Achievement drive	0.823	Judgment	0.963	Perseverance/self-regulation and control	0.935

	SM survey		Staff survey			
Rank	Competency	SM Potential improvement score	Competency	MLM Potential improvement score	Competency	OPS Potential improvement score
6	Judgment	0.818	Strategic thinking	0.944	Achievement drive	0.932
7	Interpersonal skills	0.809	Influence	0.938	Influence	0.928
8	Adaptability/flexibility	0.807	Communications	0.928	Reliability/dependability	0.918
9	Effectiveness	0.804	Problem solving	0.922	Conflict and crisis resolution / issue management	0.906
10	Organizational awareness and culture	0.802	Decision making	0.920	Effectiveness	0.905

potential behavioral competencies identified by the MLM and OPS respondents, respectively. There were no common potential behavioral competencies included in the top 10 potential competencies in the SM, MLM, and OPS respondents. Thus, the three respondent groups have somewhat different views regarding potential functional competencies for organizational performance improvement whereas they have different views regarding potential behavioral competencies for organizational performance improvement.

4.4.3 Perspective Difference of Survey Respondent Groups

Further analysis was conducted to examine differences in perspectives based on evaluation scores between the respondent groups. Table 4.7 depicts the top 10 functional and behavioral competencies with the greatest difference in evaluation scores among the respondent groups. Statistical analysis based on the impact ratings of competencies was conducted to compare group means using a *t*-test and an *F*-test. An unpaired *t*-test assuming unequal variance was performed to determine if there is a statistically significant difference between the mean values of each respondent group's evaluation scores since the respondents were from different populations. The null hypothesis is that there is no difference between the means/variance of the groups, which will be rejected at a significance level (p-value = 0.05) of 5% (i.e., 95% confidence level).

Among the 10 functional competencies presented in Table 4.7, "management and support of diversity," "communications management," "product engineering," "process engineering management," "management effectiveness/excellence," and "project change management" showed statistically significant differences between the perspectives of the respondent groups. In addition, five out of 10 behavioral competencies that include "assertiveness," "influence," "decision-making," "interpersonal skills," and "results orientation" showed statistically significant

Table 4.7 Top 10 functional and behavioral competencies with a great difference in evaluation scores

Rank	Competency	Evaluation score			Difference (Max-min)	*t*-value[a]	*F*-value[b]
		SM	MLM	OPS			
	Functional competency						
1	Management and support of diversity	0.470	0.579	0.808	0.338	**3.94**[c]	2.23
2	Construction technology and integration management	0.374	0.539	0.675	0.301	1.52	1.66
3	Interface management	0.458	0.547	0.685	0.227	1.42	2.32
4	Communications management	0.561	0.561	0.787	0.226	**2.15**[c]	1.41
5	Materials management	0.396	0.574	0.614	0.217	0.83	1.47
6	Product engineering	0.501	0.542	0.713	0.212	**1.93**[c]	0.74
7	Project cost management	0.843	0.670	0.635	0.208	1.39	**3.75**[d]
8	Process engineering management	0.473	0.560	0.677	0.204	**3.31**[c]	1.69
9	Management effectiveness/excellence	0.723	0.541	0.672	0.182	1.56	**2.69**[d]
10	Project change management	0.820	0.640	0.707	0.180	0.88	**4.41**[d]
	Behavioral competency						
1	Judgment	0.775	0.687	0.967	0.280	1.36	1.21
2	Assertiveness	0.758	0.685	0.964	0.279	**1.91**[c]	1.38
3	Influence	0.904	0.626	0.888	0.277	0.18	**2.95**[d]
4	Decision-making	0.869	0.731	0.978	0.247	**2.28**[c]	2.66
5	Analytical ability/thinking	0.827	0.703	0.950	0.246	1.68	1.36
6	Conflict and crisis resolution/ Issue management	0.804	0.650	0.867	0.217	1.14	1.70
7	Organizational awareness and culture	0.634	0.622	0.827	0.205	1.37	0.83
8	Strategic thinking	0.683	0.750	0.877	0.195	0.59	1.12
9	Interpersonal skills	0.881	0.757	0.950	0.193	**1.85**[c]	0.77
10	Results orientation	0.815	0.668	0.850	0.183	0.91	**2.96**[d]

Note: The *t*-test and *F*-test values in bold are the competencies that show statistically significant differences between the perspectives of the groups.

[a]*t*-values are calculated based on impact scale.

[b]*F*-values are calculated based on impact scale.

[c]Indicates that the difference between the mean values of the evaluation scores of the respondent groups were statistically significant at $p < 0.05$.

[d]Indicates that the difference between the variances of evaluation scores of the respondent groups were statistically significant at $p < 0.05$.

differences between the perspectives of the respondent groups. Thus, identifying the competencies for which there are differences in evaluations will help to minimize the sources of differences among SM, MLM, and OPS, leading to an improved understanding of the target areas that need to be improved to increase organizational performance.

4.4.4 Relationship Between Organizational Competencies and Organizational Performance

This section presents the results of the correlation analysis to investigate the relationships between organizational competencies and organizational performance. Pearson correlation analysis was performed in order to assess the relationship between organizational competencies and organizational performance metrics. First, a performance metric is calculated based on the average of its performance metric categories. For example, PerM is calculated based on the mean (average) of the following metrics subcategories: employee satisfaction, customer satisfaction, and competitiveness. However, each performance metric category has different performance metrics with different ranges of KPI, KPO, or PerM values. Therefore, for calculation of each performance metrics category, KPI, KPO, or PerM in that category is normalized in order to achieve a value between 0 and 1 and then the average of the normalized performance metrics is calculated. For example, competitiveness is calculated as the mean (average) of the following metrics: company image/reputation, competitive advantage, and market advantage. The actual operational/organizational-level KPI and KPO data collected from the participating company are for a single year; hence, the data show no variability where standard deviation is equal to zero for these metrics. Therefore, Pearson correlation analysis cannot be performed for factors for which the denominator of the division operation is equal to zero (see Equation 4.15). Pearson correlation analysis can be performed for these factors (e.g., market performance, financial stability, profitability ratio, growth, business efficiency) in the future if data that covers multiple years are available and upon collecting data from multiple organizations. Table 4.8 presents the results of the Pearson correlation analysis between organizational competencies and organizational performance metric categories.

Table 4.8 Correlation coefficients ($\boldsymbol{\rho}$) of organizational competencies: Organizational performance metric categories

Competency categories	Organizational-level	Project-level	
	PerMs	KPIs	KPOs
Functional	***0.637***	***0.545***	***0.671***
General administration competencies	0.562	0.543	0.629
Technical competencies	0.555	0.569	0.575
Cross-functional competencies	0.631	0.429	0.556
Production/operations competencies	0.475	0.482	0.550
Project management competencies	0.566	0.435	0.579
Supervisory/managerial competencies	0.566	0.464	0.666
Behavioral	***0.636***	***0.482***	***0.583***
Organizational attributes	0.598	0.488	0.577
Top management competencies	0.573	0.441	0.582
Middle management competencies	0.587	0.419	0.433
First-line management competencies	0.523	0.399	0.510
Individual/personal competencies	0.565	0.366	0.471

In Table 4.8, each value represents a correlation coefficient of one competency category to one performance metric. For example, the correlation of cross-functional competencies to PerMs (column 2) is 0.631. Each correlation coefficient represents the strength and direction of the relationship between a competency category and organizational performance metric. The values shown in Table 4.8 indicate that functional competencies have a moderate to strong relationship with PerMs and project-level KPIs and a strong relationship with project level-KPOs. For instance, cross-functional competencies show a moderate relationship (0.429) with project KPIs but a strong relationship with PerMs and project-level KPOs. The results in Table 4.8 also indicate that only production/operations competencies have moderate relationship (0.475) with PerM while the other functional competencies showed strong relationship. Behavioral competencies have strong relationship with PerMs and a moderate to strong relationship with project-level KPIs and KPOs. In terms of the lowest correlation coefficient, individual/personal competencies have moderate relationship (0.366) with project-level KPIs while middle management competencies show moderate relationship (0.433) with project-level KPOs. Thus, it is suggested that the company designs its policies and procedures to improve those competencies that exhibit moderate relationship with performance metrics, for example, improving cross-functional and individual/personal competencies enables to ensure a better performance in terms of project KPIs.

The overall performance of the organization is calculated as the mean (average) of performance metric categories (KPIs, KPOs, PerMs). Table 4.9 shows the correlation of organizational competencies with the overall performance of the organization.

Table 4.9 Correlation coefficients ($\boldsymbol{\rho}$) of organizational competencies: Overall organizational performance

Organizational competency categories	Overall organizational performance
Functional	***0.623***
General administration competencies	0.611
Technical competencies	0.526
Cross-functional competencies	0.579
Production/operations competencies	0.504
Project management competencies	0.577
Supervisory/managerial competencies	0.653
Behavioral	***0.654***
Organizational attributes	0.631
Top management competencies	0.624
Middle management competencies	0.576
First-line management competencies	0.538
Individual/personal competencies	0.523

All organizational competencies have a strong positive relationship with the overall organizational performance. The strongest relationship is related to supervisory/managerial competencies (0.653 for functional competencies) and organizational attributes (0.631 for behavioral competencies). The weakest relationship was observed for production/operation competencies (0.504 for functional competencies) and individual/personal competencies (0.523 for behavioral competencies). Findings from this result suggest that company policies be directed to place a greater focus on enhancing competencies such as production/operations and individual/personal competencies in order to further improve overall organizational performance.

4.5 Discussions

All the SM, MLM and OPS respondents perceived "commitment to safety" as the most critical functional competency influencing organizational performance. Furthermore, "project health and safety management" was identified as second and third ranking critical competency influencing performance by OPS and MLM, respectively. The findings are in line with Aksorn and Hadikusumo (2008) and Raoufi and Fayek (2018) which identified "appropriate safety education and training" and "safety precautions," respectively among the top three major factors influencing performance. The result further indicates that the company under study had a high safety culture and that all the survey respondents perceive commitment to safety as a critical competency. In addition, "quality of work" was ranked second by both SM and MLM while it was identified as the third ranking critical functional competency by OPS. Thus, the result showed consistency among the respondent perspectives regarding quality of work to maintain high standard in executing design, construction, and other related works. There was no common competency identified in the top three ranking behavioral competencies; hence, the respondent groups showed different views related to critical behavioral competencies influencing performance.

SM and MLM identified "project procurement management" as the top and second ranking functional competency, respectively as having a high potential for improvement in organizational performance. Likewise, "materials management" was considered as the top and third ranking functional competency by MLM and OPS, respectively as having a high potential for performance improvement. However, "management effectiveness/excellence" was perceived by OPS as having a high potential for improvement in organizational performance. "Leadership," "results orientation," and "attention to detail" are the top-ranking behavioral competencies with a high potential for performance improvement identified by SM, MLM, and OPS, respectively. "Innovation" is identified by SM and MLM as the second ranking behavioral competency with a high potential for performance improvement. These results indicate that organizational performance may improve with increasing the competencies identified as having a high potential for performance improvement. The identification and awareness of those competencies that may contribute to significant performance improvements might help management (board or top management) to direct company policies and procedures towards these competencies.

The *t*-test and *F*-test results revealed perspectives differences among respondents although the comparative analysis suggest high agreement on most of the critical competencies influencing performance. Statistically significant differences were reported between different generations of craft workers (Dai and Goodrum 2012), foremen and craft workers (Dai et al. 2007), union and non-union craft workers, and trades (Dai et al. 2009), project managers and trades (Tsehayae and Fayek 2014), supervisors and craftspeople (Raoufi and Fayek 2018). There were statistically significant differences between each group's perspectives in terms of the mean and variance of the evaluation scores. For instance, OPS ranked highly for "management and support of diversity," "communication management," "product engineering," and "process engineering" as the most critical functional competencies influencing performance while SM did not perceive these competencies as such critical. Likewise, SM ranked highly of “project cost management” and “project change management” while OPS did not see these competencies as critical influencing performance. On the other hand, “assertiveness,” “influence,” “decision making,” “interpersonal skills,” and “results orientation” are the behavioral competencies that showed significant difference among respondent groups. Thus, it is important to focus on the competencies that showed significant difference and investigate the sources of difference before implementing improvement strategies.

The Pearson correlation analysis showed a positive relationship between organizational competencies and organizational performance. The findings indicate that, an increase in organizational competencies (functional and behavioral competencies) enable improvement of organizational performance. While all organizational competencies have a strong positive relationship with the overall performance of the organization, the strongest relationship is related to supervisory/managerial competency (functional) and organizational attributes (behavioral). The weakest relationship was observed for production/operation competencies (functional) and individual/personal competencies (behavioral). Thus, it is important that company policies be directed to place a greater focus on enhancing competencies identified as having low maturity/agreement but exhibit strong relationship in order to further improve overall organizational performance.

4.6 Chapter Summary

This chapter presents a comparative analysis to identify organizational competencies influencing organizational performance. In addition, competencies that have a great potential for organizational performance improvement are also identified. Moreover, differences in respondents' perspectives on competencies influencing organizational performance and competencies having a great potential for performance improvement are investigated. Pearson's correlation analysis was performed to assess the relationship between organizational competencies and organizational performance.

A comparative analysis was conducted for the perspectives of SM, MLM, and OPS regarding the common critical competencies that influence performance. The results showed that respondents have highly similar views regarding common critical behavioral competencies and somewhat similar views regarding functional competencies. A comparative analysis regarding potential competencies for performance improvement was also conducted. Accordingly, few common competencies appeared in the top ten competencies between the three respondent groups. Although the results of the comparative analysis suggest an agreement among the perspectives of respondent groups, the results of both the *t*-test and *F*-test indicate that there were statistically significant differences between each group's perspectives in terms of the mean and variance of the evaluation scores. These statistical tests consider the sample size in calculating the critical values (i.e., t-critical and F-critical) and are thus able to identify if there is a significant difference among the perspectives of respondent groups, even if the respondents' sample sizes are small. However, because of the limitation in the sample size of SM respondents, the results associated with this group are limited and should not be generalized to the entire construction industry.

The results of the Pearson correlation analysis show that all organizational competencies have a strong positive relationship with the overall performance of the organization. A strong positive relationship indicates that the increase in competency results in an increase in performance. For example, organizational competencies have a moderate to strong positive relationship with operational/organizational-level PerMs as well as project-level KPIs and KPOs (see Table 4.10). These findings indicate that, an increase in organizational competencies (functional and behavioral competencies) enable improvement of organizational performance.

The contributions of this chapter are fourfold. First, this chapter provides a methodological approach for identifying and measuring organizational competencies adopting a comprehensive and hierarchical category of competencies to capture the multi-level nature of organizations. The comprehensive hierarchical set of competencies provides researchers and industry practitioners with a broader view of competencies affecting organizational performance. Second, this chapter presents a methodology to evaluate and rank critical competencies influencing performance and competencies with a high potential for improvement in performance. Third, this chapter compares the differences among the perspectives of the respondent groups i.e., SM, MLM, and OPS on the critical competencies influencing organizational performance that can help management in developing performance improvement strategies. Fourth, the Pearson correlation analysis identified both the strong and weak relationships of organizational competencies to overall organizational performance. The findings help both construction organizations and construction practitioners to maintain competencies with strong relationship while preparing improvement strategies for those competencies showing weak relationship with organizational performance. Thus, company policies and strategies be directed to place a greater focus on enhancing competencies that have a high impact but weak relationship with performance in order to further improve overall organizational performance.

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Chapter 5 Hybrid Neuro-Fuzzy Modelling Methodology[4]

5.1 Introduction

In this chapter, the overall methodology and detailed steps for developing the hybrid NFS model to analyze organizational competencies and predict multiple organizational performance metrics are presented. The model developed in this research is a hybrid GA-MANFIS that combines the optimization capacity of GA and the ability of MANFIS in handling multiple outputs in modeling MIMO problems. The methodology is illustrated in Figure 5.1 and the details are described in the following sections.

5.2 Identify Organizational Competencies and Performance Metrics and Collect Data

The identification and data collection of organizational competencies and performance metrics as well as results of the comparative and correlation analysis are discussed in Chapter 4. Therefore, the 60 organizational competencies (i.e., 32 functional and 28 behavioral competencies) common to both the SM and staff surveys identified in Chapter 4 are used for model development. Actual

[4] Parts of this chapter have been published in the Proceedings of FUZZ-IEEE International conference on fuzzy systems: Tiruneh, G. G. and A. R. Fayek. 2019. "Feature selection for construction organizational competencies impacting performance." *Proc. FUZZ-IEEE Int. Conf. Fuzz. Syst.*, New Orleans, LA., USA, 05 pages; submitted for publication in the *Journal of Computing in Civil Engineering*: Tiruneh, G. G., and A. R. Fayek. 2021. "Hybrid GA-MANFIS model for organizational competencies and performance in construction." *J. Comput. Civ. Eng.*, 43 manuscript pages, submitted Jan. 15, 2021.

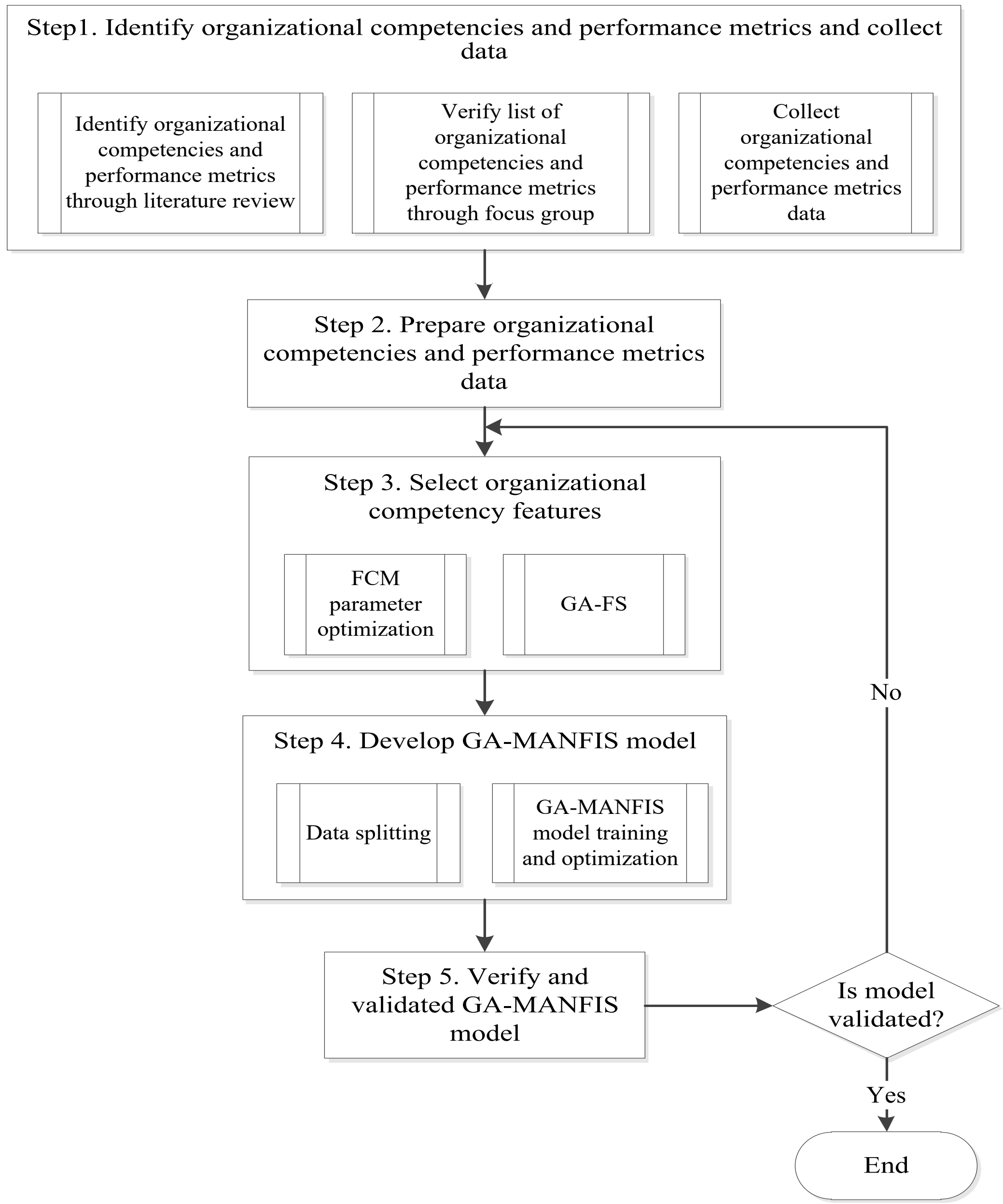

Figure 5.1. GA-MANFIS modeling methodology for construction organizational competencies and performance

company performance metrics data collected related to KPIs and KPOs are limited as they are obtained only for a single year; hence, lacks data variability and sufficiency for modeling purpose. Thus, subjective performance metrics that have sufficient data collected via the online survey were used for model development. As a result, six organizational performance metrics that include employee satisfaction, customer satisfaction, competitiveness, quality of work, safety performance, and effectiveness of planning are considered for modeling.

5.3 Prepare Organizational Competencies and Performance Metrics Data

Data preprocessing techniques for modeling include data cleaning and data transformation. These data preprocessing steps are usually implemented prior to any data-driven system modeling in order to eliminate responses or data instances that include outliers (i.e., noisy data), missing values, or bad data (Acampora et al. 2014; Cheng et al. 2015; Fattahi et al. 2018). This step ensures that the raw data collected or retrieved from the database and/or obtained from actual company and project documents is suitable for modeling. Once the data is cleaned, the next stage is performing normalization to transform the dataset in the range of [0 1]. Efficiency and accuracy of any estimating algorithm are highly dependent on the accuracy of the original or experimental data used to develop the predictive model (Tahmasebi and Hezarkhani 2012). To simplify and enhance the training performance and improve prediction accuracy, the data for both input and output variables are normalized in the range of [0 1] using Equation (5.1). Furthermore, normalizing the input-output data helps to avoid domination of attributes in greater numeric ranges over smaller numeric ranges and to avoid numerical difficulties (Cheng and Roy 2010).

$$x_N = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{5.1}$$

where, x_i and x_N are the original and normalized values, respectively, while x_{min} and x_{max} are the minimum and maximum values of x, respectively.

5.4 Select Organizational Competency Features

Once the data are cleaned, the number of input variables must be reduced using dimensionality reduction techniques to increase the accuracy of the predictive model. FS is an important and frequently used technique to reduce data dimensionality and obtain reduced data representation (i.e., features or data attributes) while producing the same or similar results (Cheng et al. 2015; Tiruneh and Fayek 2019). FS reduces computational time, thus improving model performance (e.g., predictive accuracy and interpretability) and removing redundant or noisy attributes (Cheng et al. 2015; Tiruneh and Fayek 2019). In this research, an FCM-based fuzzy inference system (FIS) that incorporates an evolutionary search method, GA, is used to identify the best subset of data for which the predictive model has the highest accuracy (e.g., the lowest RMSE). Figure 5.2 presents the steps for FS to identify representative input features. Prior to GA optimization, FCM parameters (number of clusters c, and fuzzification coefficient m) are optimized. Then an FIS is developed using the optimized FCM parameters. Finally, the FIS is used to conduct GA-based FS, which is implemented through the following steps (see Figure 5.2):

1. Randomly generate an initial subset of the population, or system variables, represented by binary strings of zeros and ones.
2. Evaluate the compatibility of each chromosome using the fitness function, which is usually the RMSE, as expressed in Equation (5.2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_t - x_p)^2} \tag{5.2}$$

   where, x_t and x_p are the actual/target and predicted values of x, respectively while N is the number of data instances.

3. A new generation or population is created based on the fittest individual from the previous generation using the three genetic operators of selection, crossover, and mutation.

4. Parents of the generated population (i.e., old chromosomes) are replaced in the new generation partially or fully by the new best offspring chromosomes.
5. Steps 2–4 are repeated until the termination condition is satisfied. The chromosome with the highest accuracy in the last generation (i.e., the organizational competencies) represented by ones are selected as the best subset of system variables for model development.

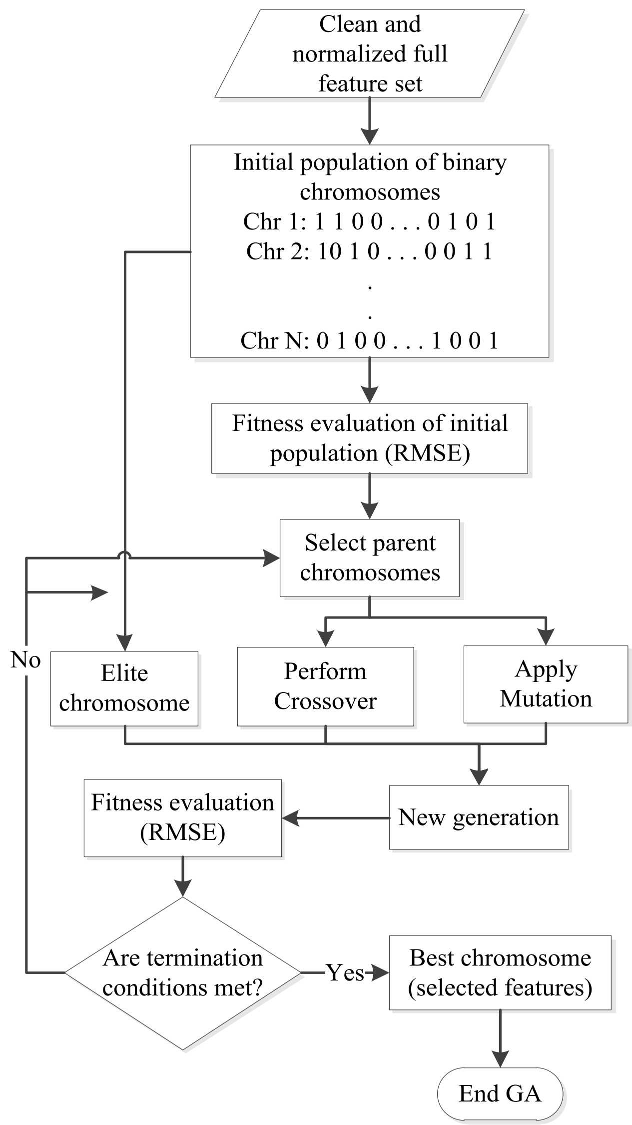

Figure 5.2. FS using GA optimization

5.5 Development Hybrid GA-MANFS Model

In this Section, the hybrid NFS model i.e., a hybrid GA-MANFIS model for organizational competencies and performance was developed using model input variables obtained from the GA-FS. The core of the modeling framework is a processing layer that contains a number of ANFIS modal blocks, which each corresponds to a single output (Das and Winter 2016; Malik and Arshad 2011). Thus, every single ANFIS in a MANFIS predicts a single output as shown in Figure 2.2 (Benmiloud 2010; Das and Winter 2016; Malik and Arshad 2011). The model development process is performed in three steps: data splitting; model development and optimization; and model verification and validation. The model development steps depicted in Figure 5.3 are discussed below.

5.5.1 Data Splitting

The first step of GA-MANFIS model development is preparing the input variable data identified from the GA-FS. These data are then randomly divided into training and testing datasets. The training data are applied in the MANFIS learning process to predict model outputs, whereas the testing data are applied to the trained model to evaluate its prediction performance. To ensure the training data are chosen randomly, all data are shuffled in rows before the training and testing datasets are selected. Past studies used different ratios of training to testing data for modeling purposes, depending on the availability of data. The most common ratio of data percentages applied for model development (training data) to model validation (testing data) is 70/30. However, many studies that developed limited-data models used a ratio of 80/20 for training to testing data (Fattahi et al. 2018; Agah and Soleimanpourmoghadam 2020). Some studies even used a ratio of 85/15 for training to testing data (Cheng and Roy 2010; Tahmasebi and Hezarkhani

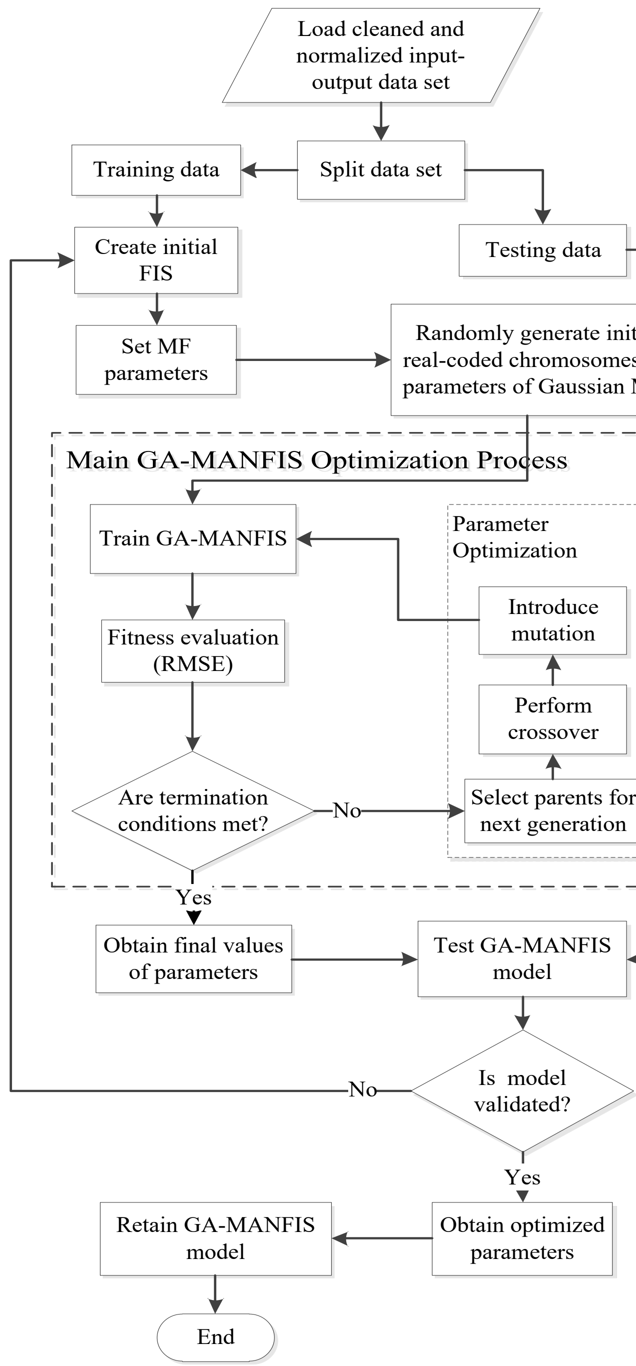

Figure 5.3. GA-MANFIS model training and optimization

2012). For example, Cheng et al. (2010) used 25 training data and 3 testing data to develop a model that can help construction project stakeholders to estimate construction cost. In this research, a ratio of 80/20 is used for model development.

5.5.2 GA-MANFIS Model Training and Optimization

ANFIS is a building block of MANFIS. For *K* outputs, there will be *K* number of ANFIS modal blocks in the MANFIS model (Cheng et al. 2002; Das and Winter 2016; Malik and Arshad 2011). The selected input features and the optimized FCM parameters are used to develop the MANFS model. First, an FCM-based initial FIS is created to develop the ANFIS modal blocks for each output. Then, the ANFIS modal blocks are incorporated into the MIMO modal block (Figure 2.2). Finally, the MANFIS model is trained using GA optimization as shown in Figure 5.3. Model development, training, and optimization procedures are discussed as follows.

5.5.2.1 Create FCM-based Initial FIS

Creating an FCM-based initial FIS is the first step in developing the GA-MANFIS model. FCM clustering results in the development of a partition matrix ($\boldsymbol{U} = [u_{ik}]$) that includes the data points in each cluster (Pedrycz 2013). Furthermore, FCM clusters the input-output dataset into c numbers of clusters ($\boldsymbol{V} = [v_j]$) by determining a prototype (cluster center) for each cluster. Fuzzy partitioning is carried out through an iterative optimization by updating the partition matrix u_{ik} and cluster centers v_j using Equations (5.3) and (5.4), respectively (Pedrycz 2013).

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{2/m-1}}, \; i = 1, \dots, c, \;\; k = 1, \dots, N \tag{5.3}$$

$$v_j = \frac{\sum_{k=1}^{N} u_{ik}^{m} x_k}{\sum_{k=1}^{N} u_{ik}^{m}}, \; i = 1, \dots, c, \;\; k = 1, \dots, N \tag{5.4}$$

The FCM clustering algorithm maximizes the membership degree of each data point close to the cluster center, while minimizing the membership degrees of the data away from the cluster center (Elbaz et al. 2019). This method allows the development of data-driven FIS using rules for defining the relationships between input and output variables (Pedrycz 2013). Accordingly, the input-output data set, in the form (x_i, y), i = 1, 2, …, N, where input variables (competencies) as $x_i = [x_{1i}, x_{2i}, \ldots, x_{ki}]$ and output (organizational performance) as $y = [y_i]$, is combined to form the (N + 1)−dimensional vector $\boldsymbol{p} = (x_i, y)$. Then, using FCM clustering, c prototypes $\{v_1, v_2, \ldots, v_j\}$ and a partition matrix $\boldsymbol{U} = [u_{ki}]$ representing the membership degree of a data instance in the j^{th} cluster are developed by applying Equation (5.3) in the product space of $\boldsymbol{X}\times\boldsymbol{Y}$. The process results in c prototypes, each of which has an MF and corresponding to each of the fuzzy rules R_j, j = 1, 2, …, c. Then, projecting the prototypes on the output space $\boldsymbol{Y}$ by considering their last coordinates as v_1 [y], v_2 [y], …, v_j [y] results in the MFs of the output variable, which are denoted as B_1, B_2, …, B_j. Similarly, projecting the prototypes on the input space $\boldsymbol{X}$ as v_1 [x], v_2 [x], …, v_j [x] results in the MFs of the input variables, which are denoted as A_1, A_2, …, A_j. Each cluster represents a fuzzy rule; thus, FCM clustering results in the development of c number of fuzzy rules in the form of "R_j: If X is A_j, then Y is B_j, j = 1, 2, …, c." An example of a fuzzy rule is shown below, where words in italics are the features (i.e., competencies) and the variables are shown in bold:

If *interdisciplinary alignment* is **poor** and *project safety management* is **average** and *project cost management* is **high** and *technical knowledge* is **good** and *motivation* is **low** and *commitment* is **average** then *quality of work* is **average** and *competitiveness* is **low**.

The initial FCM-generated FIS is used to develop ANFIS modal blocks for each output (Figure 2.2). Two types of FIS (i.e., Mamdani and Takagi-Sugeno) have been widely used in various applications. In Mamdani FIS, both the condition and consequent of the system are represented as a fuzzy set; hence, needs defuzzification to obtain a crisp output value (Pedrycz 2013). In the case of Takagi-Sugeno FIS, the conclusion is represented using a function; either a zero- or first-order polynomial function that fits the model output data in the region specified by the fuzzy Cartesian product of the condition fuzzy sets is used (Pedrycz and Gomide, 2007). Mamdani FIS are intuitive and have better interpretability (i.e., explicit knowledge representation). On the other hand, Takagi-Sugeno FIS have capability for numeric processing (i.e., accuracy of prediction). In this research, Takagi-Sugeno FIS is used because of its superior performance in terms of accuracy. Although they are automatically generated and tuned during the learning processes, it is important to set the type of parameters, or MFs, that represent the variables. Different realizations of MFs exist (e.g., triangular, trapezoidal, Gaussian, and bell shaped). According to Elbaz et al. (2019), there are no explicit methods or formula for predicting the necessary type MFs. Studies have indicated that Gaussian MFs are a better option because they are efficient with higher performance in prediction for their continuity and smoothness, simplicity in representation (only two parameters are required, modal value μ representing the typical value and σ representing the spread), ease of construction using a data-driven approach, faster convergence during optimization of membership functions, and suitability for models that seek high-control accuracy (Elbaz et al. 2019; Siraj et al. 2016). In this research, Gaussian MFs based on Equation (5.5) have been used for representing model input variables. The Gaussian MF parameter σ represents the standard deviation, denoting the spread of A, and μ represents the modal value, denoting the typical element of A.

$$A(x, \sigma, \mu) = e^{-(x-\mu)^2/(2\sigma^2)} \tag{5.5}$$

Figure 5.4 shows a fuzzy set A, representing a linguistic variable is characterized using its MF which represents numerically the degree to which an element x belongs to the fuzzy set and fits the linguistic variable over a continuous range A: $X \rightarrow \mu$ = [0 1]. For example, Figure 5.4 shows an example of a fuzzy set which characterize organizational competencies, say *technical knowledge* or *interdisciplinary alignment* using linguistic variables *low*, *average*, and *high*.

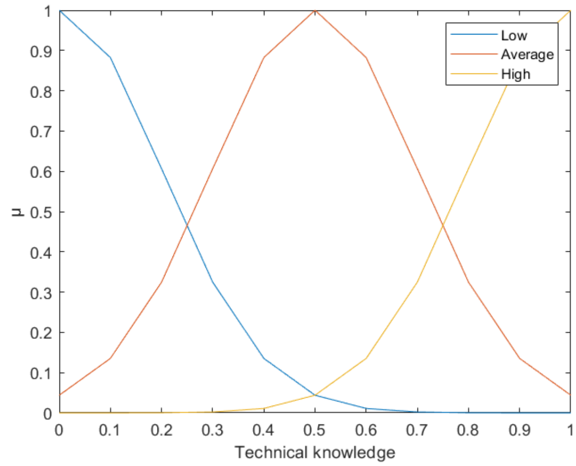

Figure 5.4. Gaussian MF for fuzzy set representing "*technical knowledge*"

5.5.2.2 GA-MANFIS Model Training and Optimization

The use of GA optimization enables the MANFIS training to optimize the parameters of input-output in the system (i.e., premise and consequent MFs). The process of GA optimization follows a similar approach as described above in Section 5.4. The only difference at this stage is that real-coded parameters are used to represent model input variables instead of binary coded strings. For FS, binary coded chromosomes of the GA represent individual features or variables (i.e., organizational competencies) using zeros or ones. However, model input variables are further represented by a number of parameters or MFs. Furthermore, Kumar and Hynes (2020) indicated that the use of real-coded parameters helps to obtain the optimal solution in the least number of iterations. Thus, the variables are represented by a real-code (i.e., real numbers) that encodes the parameters of the MANFIS with a corresponding range of input parameter value. Each chromosome (individual) consists of several genes that represent the network's parameters. The premise and consequent parameters are updated by the GA during the learning process. The RSME is commonly used as the fitness or cost function for GA that utilizes a training dataset for optimizing MANFIS parameters (Kaveh et al. 2018). The learning and parameter optimization process of the MANFIS network terminates when the fitness error measure, RMSE, between two consecutive iterations is reduced to a satisfied level, which is the set threshold of 10^{-5}.

5.6 Verify and Validate GA-MANFIS Model

Oberkampf et al. (2004) stated that verification is the process of determining that a model's implementation accurately represents the developer's conceptual description of the model. According to Lucko and Rojas (2010), verification confirms the technical correctness of a model in accordance with its established specifications; that is, model verification is conducted to ensure that model components are working as expected. To verify the GA-MANFIS model, all mathematical equations and components of the model, such as MATLAB codes, are checked for their correctness. Further, running the model multiple times to check for the replicability of its results as well as use of tracing and plot graphs is conducted to track changes in the variables of the model.

The model is validated to determine how well it reflects a real-world system (Oberkampf et al. 2004). To validate the GA-MANFIS model, conceptual validity and data validity are conducted. Conceptual validity refers to basing the model on factors identified from literature that were validated by construction experts and practitioners through a focus group. Data is validated through pilot testing of a data collection protocol and by following a structured data collection methodology, testing for construct validity, and testing the reliability of the data-collection measures. The GA-MANFIS model performance is evaluated by comparing the model outputs (i.e., predicted results) against the testing dataset. The RMSE expressed in Equation (5.2) is used as the fitness or cost function to check the conformity of the predicted values with the actual observed or measured values with a minimum RMSE. Additionally, sensitivity analysis is conducted to determine whether the model behaves realistically, by changing model parameters and evaluating changes in the behavior of model output.

5.7 Chapter Summary

This chapter presented a methodology for developing hybrid NFS model to analyze organizational competencies and predict multiple organizational performance metrics. A GA-based FS is implemented to identify organizational competencies to be considered as model inputs for the hybrid NFS model development. Furthermore, a methodology to develop a hybrid GA-MANFIS for organizational competencies and performance is presented.

The main contributions of this chapter can be grouped into three areas. First, the chapter provides a modeling approach for organizational competencies and performance that can be applied for organizations in the construction industry. Second, the chapter provides a hybrid NFS modeling approach that can model MIMO problems inherent in construction and predict multiple performance metrics simultaneously. Third, it contributes to the advancement of the state of the art in NFS modeling for organizational competencies and performance by (i) providing a GA-FS methodology to reduce the dimensionality of data that enables to develop a concise model with improved accuracy; (ii) providing a method for modeling MIMO problems using MANFIS that can handle multiple outputs; and (iii) implementing evolutionary optimization for parameter/MF optimization and model training using GA optimization to enhance the prediction performance of the mode. The next chapter presents a case study to illustrate the application of the proposed GA-MANFIS modeling methodology for organizational competencies and performance in construction.

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Chapter 6 Construction Application and Model Validation: Case Study[5]

6.1 Introduction

In this chapter, the modeling approach proposed in Chapter 5 was applied to develop a hybrid GA-MANFIS model for analyzing organizational competencies and predict organizational performance. Although MANFIS is widely used in research disciplines other than construction, limited research has been conducted in the construction domain which is characterized by complex and nonlinear multiple input-output relationship of real-world problems. To date, there have been few studies on MIMO NFS for modeling construction problems specifically for predicting multiple performance metrics. As such, there remains a need for developing modeling approaches that can handle complex and nonlinear MIMO performance prediction problems. To address the need for developing modeling approaches that can handle complex, non-linear MIMO performance prediction problems and improve effectiveness of handling multiple outputs for construction applications, this research proposes a novel methodology for developing a hybrid GA-MANFIS model for construction organizational competencies and performance. Thus, the objectives of this chapter include (1) illustrate the modeling methodology presented in chapter 5 with a case study for developing a hybrid GA-MANFIS modeling approach which can handle MIMO problems inherent in construction processes and practices, (2) relate organizational competencies with performance, and predict multiple organizational performance metrics using organizational competencies, (3)

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provides a GA-based FS approach to reduce dimensionality of data, which enables the identification of organizational competencies that have significant influence on organizational performance.

The rest of this chapter is structured as follows. First, data pre-processing for model development is presented. Second, the results of the GA-based FS steps involved in identifying model input variables are presented. Third, the procedure in developing the GA-MANFIS model is explained. In addition, model training and optimization results are presented and discussed. Finally, the verification and validation process of the GA-MANFIS model is presented.

6.2 Data Pre-processing

Data collection and analysis of organizational competencies and performance metrics is presented in Chapter 4. Thus, the 60 organizational competencies (i.e., 32 functional and 28 behavioral competencies) common to both the SM and staff surveys identified in chapter 4 are used for model development. In addition, six organizational performance metrics that include employee satisfaction, customer satisfaction, competitiveness, quality of work, safety performance, and effectiveness of planning, which have sufficient data variability, are considered for modeling. Organizational competencies are the predictor variables (i.e., antecedent) to organizational performance, which is the dependent variable in the model.

Data preprocessing was implemented to eliminate responses that had outliers, missing values, and noisy or bad data, in order to facilitate modeling. Different data preprocessing techniques such as data cleaning, normalization, and FS were implemented in this study.

6.2.1 Data Cleaning

All online survey responses and actual performance data extracted from actual company and/or project documents were encoded to an Excel sheet. A total of 80 data instances were recorded and considered for model development. Then all survey responses and performance data were checked for missing values, outliers, and inconsistencies. As part of the data cleaning, survey responses and performance data with missing values and outliers are removed from the data. The data cleaning resulted in 62 data instances which were used to develop the hybrid GA-MANFIS model. Organizational competencies and performance metrics data were characterized as having: 60 input features (i.e., competencies); 6 output features (i.e., performance metrics); and 62 data instances (i.e., complete survey responses or data points). Thus, the input data matrix is 62×60 while the output data matrix is 62×6. Thus, the overall input-output MIMO system data matrix is 62×66.

6.2.2 Data Normalization

The input-output of the cleaned data were normalized using Equation (5.1) to achieve a value between 0 and 1 and to avoid domination of attributes in greater numeric ranges over smaller numeric ranges. Normalization of data also helped simplify and enhance the training and improve the performance and prediction accuracy of the model. Thus, the original cleaned data that was normalized was then used to implement the GA-based FS to reduce the dimensionality of the data.

6.3 GA-based FS

As described in Section 6.2 above, the 60 organizational competencies (32 functional and 28 behavioral competencies) were features/attributes that needed to be reduced for model development. It was evident that the dimensionality of original raw data was very high, which makes it difficult to build a concise and efficient predictive model. Therefore, GA-based FS was conducted to reduce the dimensionality of data attributes, help reduce computational time, and help improve model accuracy following the steps described in the methodology section (Section 5.4). Performing the GA-based FS encompassed implementing FCM parameter optimization and performing FS using GA optimization.

6.3.1 FCM Parameter Optimization for GA-FS

The MATLAB programming language was used to develop a code for finding the optimum value of clusters *c* and fuzzification coefficient *m*, with FCM performed on the cleaned input-output data. The optimum parameters of FCM (i.e., *c* and *m*) were obtained by running the MATLAB code multiple times. A total of 60 different runs were implemented where the minimum RMSE and FCM parameters for which the RMSE was minimum were recorded in each run. Table 6.1 shows the best results obtained from the FCM parameter optimization.

Table 6.1. FCM parameter optimization results

Code*	*c*	*m*	Minimum RMSE	Rank
Opt_S10	6	2.50	0.037141	1
Opt_Sug7	6	1.45	0.038779	2
Opt_Sug18	7	2.55	0.040223	3
Opt_S25	3	1.75	0.042300	4
Opt_Sug11	7	2.50	0.042737	5
Opt_Sug2	7	1.90	0.047960	6
Opt_Sug8	7	2.35	0.048160	7
Opt_S2	7	1.75	0.065234	8
Opt_S16	6	1.85	0.066222	9
Opt_S6	6	2.25	0.077706	10

* FCM parameter optimization run

The parameter optimization result indicated that the RMSE tended to be minimum when the values of *m* were low irrespective of the number of clusters, especially closer to 2. For FCM parameter optimization, $c = 3$ to 7 and $m = 1.25$ to 3.75 with 0.05 step were used. Accordingly, the optimum values determined for $c = 6$ and $m = 2.50$, as shown in Figure 6.1.

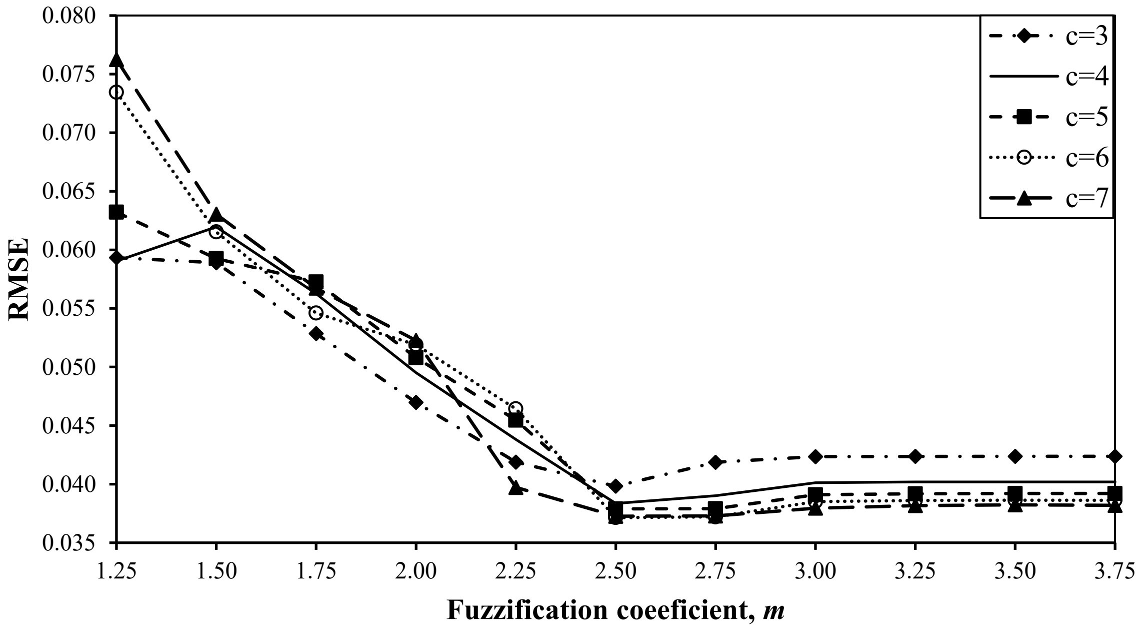


Figure 6.1. Parameter optimization result for which RMSE is minimum

6.3.2 GA-FS to Identify Model Input Organizational Competencies

Applying the optimum FCM parameters, an FIS was developed using the *genfisOptions* of MATLAB 2020b. Then FS was conducted using binary coded GA optimization on the FIS. The RMSE was used as the fitness function for GA optimization. GA selects features (i.e., competencies used as input) by optimizing the RMSE between the output of the FIS (i.e., predicted output) and the output from the actual (testing) data as a fitness value. The crossover and mutation probabilities were set as 0.8 and 0.1, respectively, while the number of generations was 100. Table 6.2 shows the results of the GA-FS ranked based on average fitness values. The top five results in Table 6.1 were considered for the GA-FS step. For each result, a population of 50, 60, 80, and 100 was used, keeping the number of generations at 100. Therefore, 20 different combinations of GA-

FS were conducted to identify the results with the best fitness values (RMSE). The values in Table 6.2 indicate that the FCM parameters that provided the best five results with minimum error during the GA-FS step were for $c = 6$, $m = 1.45$ and $c = 3$, $m = 1.75$, respectively. The results further indicated that the best optimum parameters identified in Table 6.1 (i.e., $c = 6$, $m = 2.50$) showed poor results in terms of the GA-FS fitness function (see Table 6.2). The poor performance is the result of the higher value of $m = 2.50$: as the m value gets higher, the MFs will become "spiky" (i.e., the membership grades are equal to 1 at the prototypes/cluster centers, and the values rapidly decline when moving away from the prototypes) with minimum overlap of adjacent MFs, and hence, the process provides less accurate results. Furthermore, the results showed that the number of features selected got lower as the values of m used for the FS increased. Moreover, results with the best fitness function provided almost similar numbers of features. For instance, four of the top five ranked results in Table 6.2 selected 19 features as a representative subset of the original data while the remaining result obtained 18 features. For model development, the result with lower value of c and m value closer to 2 was considered. Pedrycz and Gomide (2007) recommended that a value of $m = 2.00$ or closer is appropriate for the application of FCM clustering. Therefore, $c = 3$ and $m = 1.75$ is the optimum FCM parameter selected for GA-MANFIS model development.

After performing the FS using GA optimization, 19 competencies were selected out of 60, with the best and mean fitness values (RMSE) of 0.0386 and 0.0351, respectively (Table 6.2). More details about the GA-FS methodology can be found in Tiruneh and Fayek (2019). The list of competencies identified include: staff development (c_1); goal orientation (c_2); interdisciplinary alignment (c_3); commitment to safety (c_4); construction, production, and manufacturing (c_5); project safety management (c_6); project cost management (c_7); project procurement management (c_8); engagement (c_9); ability to build trust (c_{10}); organizational culture (c_{11}); judgment (c_{12}); values

Table 6.2. GA-FS results for the optimized FCM parameters.

FCM parameter optimization values				GA-FS result values				
Code	*c*	*m*	Min. RMSE	Population	Selected features (no.)	Average fitness (RMSE)	Best fitness (RMSE)	Rank based on average fitness
Opt_S10	6	2.5	0.037141	50	18	0.047080	0.043382	14
				60	18	0.046710	0.043402	11
				80	16	0.046881	0.043083	12
				100	15	0.046983	0.043477	13
Opt_Sug7	6	1.45	0.038779	50	22	0.043843	0.040428	8
				60	**19**	**0.040227**	**0.037340**	**2**
				80	**18**	**0.040837**	**0.036858**	**3**
				100	**19**	**0.038646**	**0.035067**	**1**
Opt_Sug18	7	2.55	0.040223	50	15	0.045183	0.049491	9
				60	16	0.047307	0.043375	15
				80	17	0.046513	0.042393	10
				100	16	0.048640	0.044637	19
Opt_S25	3	1.75	0.042300	50	19	0.042157	0.040530	7
				60	**19**	**0.041731**	**0.039895**	**4**
				80	22	0.041968	0.039813	6
				100	**19**	**0.041967**	**0.040344**	**5**
Opt_Sug11	7	2.50	0.042737	50	15	0.048054	0.043580	17
				60	16	0.049209	0.045792	20
				80	16	0.048334	0.044543	18
				100	15	0.047802	0.042622	16

and ethics (c_{13}); conflict resolution (c_{14}); results orientation (c_{15}); influence (c_{16}); communications (c_{17}); motivation (c_{18}); and perseverance (c_{19}). The reduced number of organizational competencies identified as a result of GA-FS were used as input variables for model development. Furthermore, the competencies obtained from the GA-MANFIS were the best subset of the original organizational competencies; hence, they enable development of a model that provided high accuracy. In addition to reducing the dimensionality of model input variables to develop a concise mode, the GA-FS enabled identification of organizational competencies that have a significant impact on organizational performance.

6.4 GA-MANFIS Model Development

The hybrid GA-MANFIS model was programmed in MATLAB R2020b. A Takagi-Sugeno FIS with Gaussian MFs was applied to create the initial FIS to develop the GA-MANFIS model. The 19 organizational competencies and 7 organizational performance metrics were the model input and output variables, respectively. The GA- MANFIS was designed by decomposing it into seven MISO adaptive neuro-fuzzy systems that correspond to and predict a single output. In this study, several attempts were performed in order to select the various parameter values that are required for GA to obtain the best model with optimal solutions. Thus, considering the limited data used for model development, a population size of 50, a crossover rate of 0.8, and a mutation rate of 0.1 were selected. To evaluate the model predicting performance, the RMSE was used as a fitness function. The following sections present the model architecture, input and output variables, training and optimization, and results.

6.4.1 GA-MANFIS Model Architecture

The hybrid GA-MANFIS model of construction organizational competencies and performance incudes three components: the input layer, the MIMO modal block layer, and the output layer, as shown in Figure 6.2. The input layer consists of organizational competencies obtained during the FS step that are utilized as the model's inputs. The MIMO modal block, the core of the model framework, is a processing layer that contains a number of ANFIS modal blocks, which each correspond to a single output. The number of MFs are generated automatically by ANFIS, based on the FCM-based initial FIS used to build the ANFIS. Each ANFIS in the MIMO modal block is trained and optimized in parallel and predicts a single output. In this way, the model can predict multiple outputs by using the same multiple inputs. Finally, the output layer consists of organizational performance metrics as the model's output.

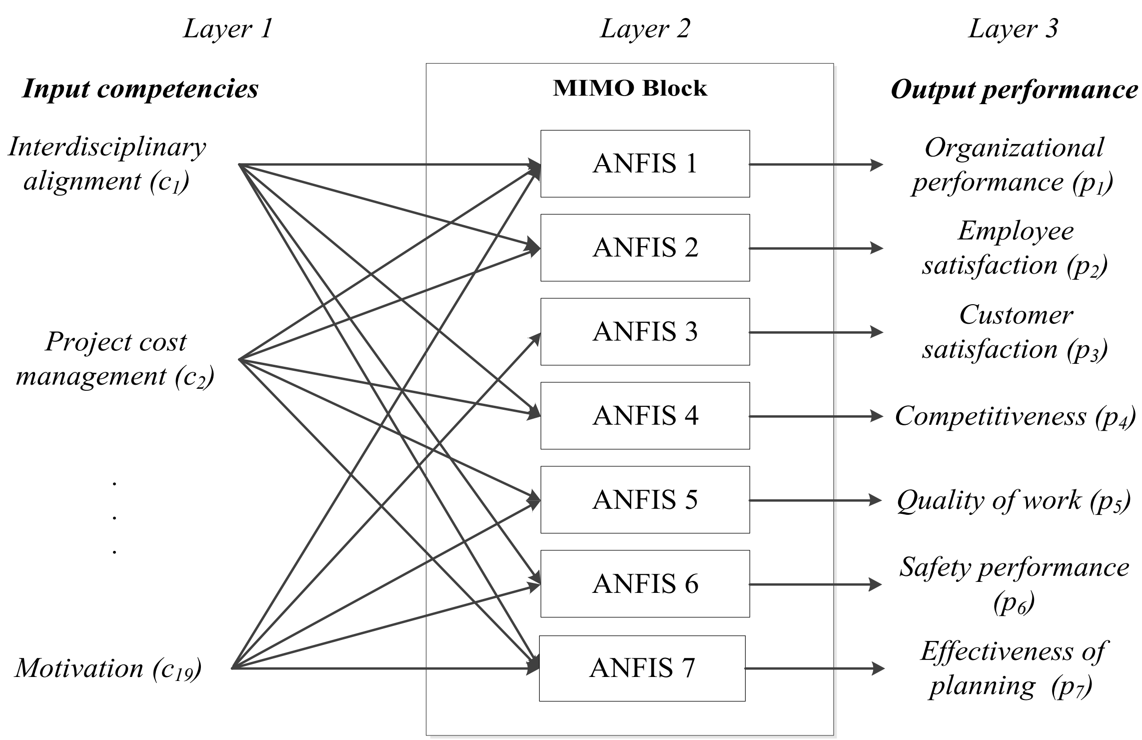


Figure 6.2. GA-MANFIS model architecture for organizational competencies and performance

6.4.2 GA-MANFIS Model Input and Output Variables

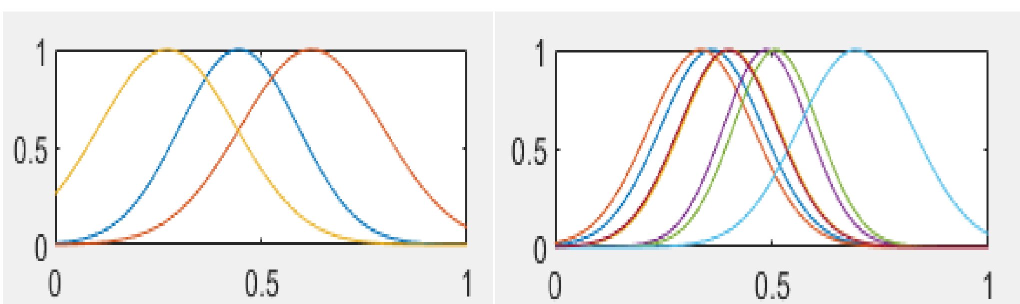
The 19 organizational competencies obtained by GA-based FS were used as input variables. As shown in Figure 6.2, organizational competencies were introduced as the input parameters into the GA-MANFIS model. Six performance metrics that include employee satisfaction (p_2), customer satisfaction (p_3), competitiveness (p_4), quality of work (p_5), safety performance (p_6), and effectiveness of planning (p_7) were identified as model outputs. A seventh model output, overall organizational performance (p_1), was added by taking the average of the normalized values of the other 6 performance metrics to determine the overall organizational performance. Thus, the MIMO modal block of the MANFIS is designed by incorporating seven MISO ANFISs.

6.4.3 GA-MANFIS Model Training and Optimization

The 62 data instances obtained from the data preprocessing stage were used for training and testing the GA-MANFIS model. All data were shuffled in rows before selecting training and testing data to ensure the training and/or testing datasets were chosen randomly. Thus, 80% (50) of the dataset was used for training the GA-MANFIS, and the remaining 20% (12) were used for validating the model. An FCM-based Takagi-Sugeno FIS was used to develop each ANFIS modal block in the MANFIS MIMO block. The real-coded GA was used to train and optimize the premise and consequent parameters (i.e., MFs of the GA-MANFIS model). As discussed in the methodology section, the crossover and mutation probabilities were set as 0.8 and 0.1, respectively, and a roulette wheel selection method was used. The learning and parameter optimization process of the GA-MANFIS network terminated when the fitness error measure, RMSE, between two sequential iterations or the maximum 100 iterations reduced to a satisfied level, which was the set threshold of 10^{-5}.

6.4.4 GA-MANFIS Model Results

In this research, 48 GA-MANFIS models were implemented for different GA parameters, such as population size and number of generations (iterations). For population size, values of 25, 50, 60, and 100 were tested; the number of generations used to run the model were 25, 50, and 100. Similarly, different initial FIS with 3, 5, and 7 clusters for developing the model were tested. The best optimized model is defined as the one that predicts the results of the test data with highest accuracy (i.e., minimum RMSE). The GA-MANFIS with a population size of 50, 100 generations, and 3 clusters was found to be the optimal model. The results indicate that increasing the number of clusters while developing a model with limited data reduces the model performance. Figure 6.3 shows the optimized MFs of interdisciplinary alignment for c =3 and c =7 obtained after the GA-MANFIS training and optimization. Moreover, an investigation of the MFs obtained for models with $c = 7$ were very close to one another and could therefore be merged to obtain better model performance. Thus, models with fewer clusters provided the best result.



a) MFs for $c = 3$ b) MFs for $c = 7$

Figure 6.3. Optimized MFs for interdisciplinary alignment for (a) $c = 3$ and (b) $c = 7$

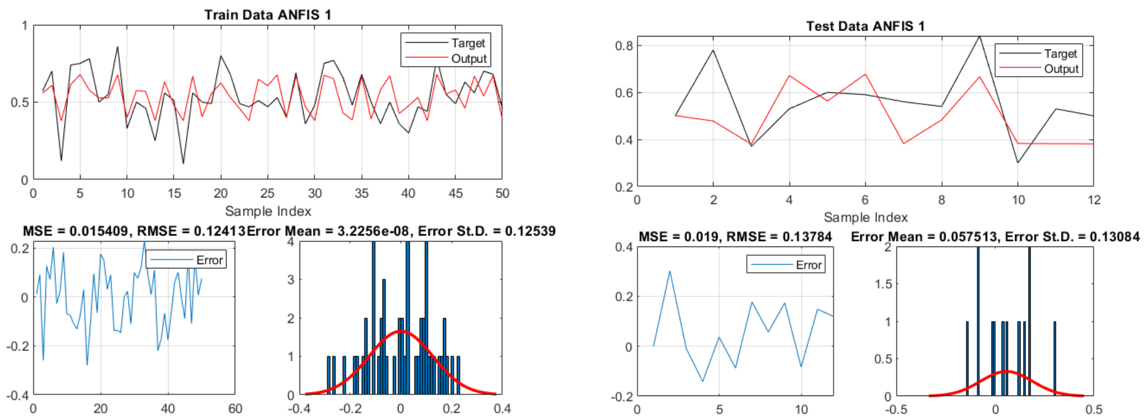
Table 6.3 presents results of the most optimal GA-MANFIS model. The values in Table 6.3 indicate that the optimal model can predict 4 of the 7 organizational performance metrics with high accuracy. The highest prediction accuracy for the testing data with a minimum RMSE = 0.13784 was obtained for *overall organizational performance*. In addition, the optimal GA-MANFIS model predicted *customer satisfaction*, *employee satisfaction*, and *effectiveness of planning* with a higher prediction accuracy. The prediction performance of the model for *quality of work* was low, with RMSE = 0.32253, compared to the other metrics. However, the predictions for *competitiveness* and *safety performance* showed better accuracy than *quality of work*, with RMSE values of 0.24507 and 0.27596, respectively.

Table 6.3. Results of optimal GA-MANFIS model outputs.

Organizational performance metrics	Training data			Testing data		
	RMSE	Error mean	Error st. d.	RMSE	Error mean	Error st. d.
Overall organizational performance	0.12413	3.22E-8	0.12539	**0.13784**	0.05751	0.13084
Employee satisfaction	0.20037	3.52E-8	0.20240	**0.18901**	0.00251	0.19740
Customer satisfaction	0.25376	0.09181	0.23896	**0.18078**	0.15063	0.10441
Competitiveness	0.21282	3.00E-8	0.21498	0.24507	0.11347	0.22688
Quality of work	0.41657	-0.27040	0.32010	0.32253	-0.12542	0.31037
Safety performance	0.29406	0.19591	0.22151	0.27596	0.13158	0.25336
Effectiveness of planning	0.23141	2.75E-8	0.22376	**0.19329**	-0.06933	0.18845

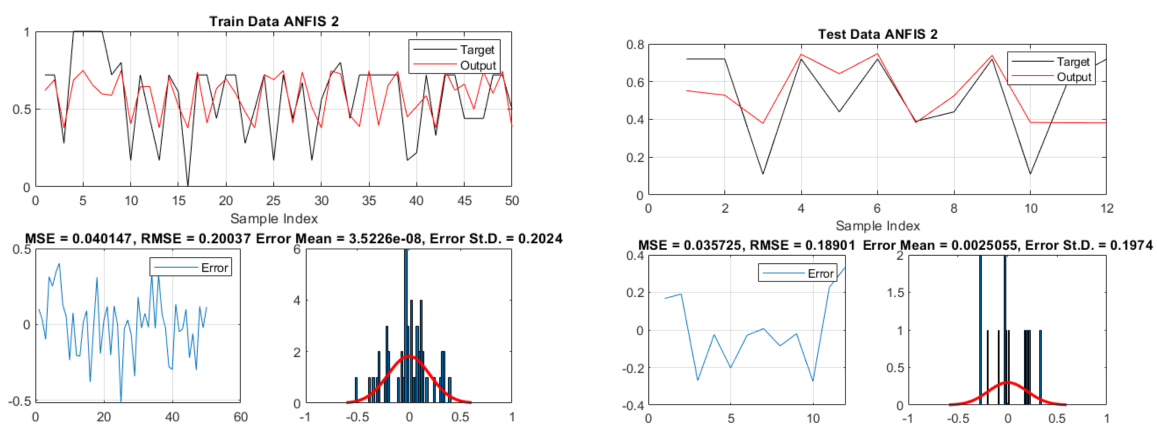
A comparison between the actual and predicted values of performance metrics by the best optimal GA-MANFIS model (i.e., model with population = 50 and generations = 100) are depicted in Figures 6.3 and 6.4. As noted in the methodology, each ANFIS modal block (Figure 6.2) corresponds to the prediction of a single output. For instance, Figure 6.4 depicts ANFIS 1 prediction of *overall organizational performance* with RMSE = 0.26406, error mean = 0.057513, and standard deviation = 0.13084 for the training data. The prediction for testing data provided RMSE = 0.13784, error mean = 0.057513, and standard deviation = 0.13084. A closer look at

Figure 6.4 further indicates that the model output value for the overall performance follows the behavior of the target or actual values of the testing data.



a) training b) testing

Figure 6.4. Comparison of target, output, MSE, RMSE, mean error, and standard deviation (St. D.) for *overall organizational performance*



a) training b) testing

Figure 6.5. Comparison of target, output, MSE, RMSE, mean error, and standard deviation (St. D.) for *employee satisfaction*

Figure 6.5 presents the prediction of ANFIS 2 for employee satisfaction with RMSE = 0.18901, mean error = 0.0025, and error standard deviation = 0.1974 for the testing data. The plots of results showed a good fit both for the training and testing data. Prediction for the remaining performance metrics was implemented in the same manner where the results showed a good fit, that is, followed the pattern of the actual target values.

In summary, the results of the GA-MANFIS shown in these figures follow the trends of the actual test data and provided a good fit for many of the organizational performance metrics. Furthermore, the GA-MANFIS showed good performance in predicting 4 of the 7 organizational performance metrics including *overall organizational performance*, *employee satisfaction*, *competitiveness*, and *effectiveness of planning*. The relatively poor fit for *customer satisfaction*, *quality of work*, and *safety performance* results from the lack of adequate variability in the data. Furthermore, the testing errors are higher than the training errors in some cases. The reason for this issue may be due to the limitation of data (i.e., lack of variability, quality, and quantity as well as discreteness of data) used for model development.

6.5 GA-MANFIS Model Verification and Validation

Model verification was conducted by checking model components such as MATLAB codes and mathematical equations to leave no doubt for any possible errors in the model. Furthermore, the model was run multiple times to check replicability of results using graphical plots. The performance of the proposed GA-MANFIS was found to be excellent compared with the target goal. The performance curves, or graphical plots, for training and testing (Figures 6.4 and 6.5) are almost identical, which indicates that the model output shows a best fit that follows the patterns of the target results (actual values).

Conceptual validity and data validity were performed for the GA-MANFIS model as described in the methodology section. In addition, the performance of the GA-MANFIS model was evaluated by comparing the model outputs (predicted results) against the testing dataset using the fitness function (RMSE) given by Equation (5.2) (see Table 6.3). Sensitivity analysis was also conducted to identify the main parameters of the GA-MANFIS model that affect the model outputs significantly. The main parameters for the GA-MANFIS are the population size and number of generations (or iterations). Furthermore, the purpose of sensitivity analysis is to determine whether the model behaves realistically by changing the main model parameters (population size, number of generations). The results of the sensitivity analysis showed that the effect of number of generations on model output was insignificant. However, changes in the population size of the GA optimization showed a significant effect on model outputs. Table 6.4 presents the sensitivity analysis of the optimal model with respect to changes in population size of the GA optimization.
The values in Table 6.4 reveal that the model's prediction accuracy decreases as the population increases. Limited data used for model development coupled with a large search space for large population size results in reduced prediction accuracy. As the size of population increases, the search space for GA to find an optimal solution becomes large, which makes the optimization processes too complicated and much too time consuming. The model prediction patterns follow a similar trend to that of the optimal model, although with reduced prediction accuracy. Thus, population size is an important factor that needs to be chosen carefully in lieu of the data availability for model development.

Table 6.4. Sensitivity analysis and comparison of best performing models.

Organizational performance metrics	RMSE							
	Population = 50		Population = 60		Population = 80		Population = 100	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Overall organizational performance	0.12413	0.13784	0.13035	0.11251	0.12925	0.09793	0.12947	0.09934
Employee satisfaction	0.20037	0.18901	0.19356	0.23850	0.18572	0.23174	0.19707	0.21448
Customer satisfaction	0.25376	0.18078	0.23836	0.25465	0.25457	0.25400	0.26481	0.16726
Competitiveness	0.21282	0.24507	0.22140	0.16173	0.22610	0.16677	0.20713	0.23690
Quality of work	0.41657	0.32253	0.40764	0.46990	0.37794	0.44287	0.39198	0.39410
Safety performance	0.29406	0.27596	0.27086	0.31270	0.31124	0.25224	0.31774	0.30462
Effectiveness of planning	0.23141	0.19329	0.23868	0.37885	0.27113	0.28610	0.27108	0.20100

For further validation, the results of the GA-MANFIS model were compared with a GA-ANFIS. For this comparison, 7 independent MISO ANFIS models were developed for each organizational performance metric and overall organizational performance. As shown in Table 6.5, the GA-MANFIS performs better than the GA-ANFIS model in predicting 5 of the 7 organizational performance metrics. For instance, GA-MANFIS showed a significant 27.62% improvement in prediction accuracy for *effectiveness of planning* and 22.38% improvement for *overall organizational performance*. GA-MANFIS obtained a better performance with 7.25%, 5.16%, and 5.06% improvement of prediction accuracy for *safety performance*, *quality of work*, and *employee satisfaction*, respectively. However, GA-ANFIS showed a better performance for *competitiveness* with 16.07% improvement of prediction accuracy, and 4.04% improvement for *customer satisfaction*.

Table 6.5. Comparison of GA-ANFIS and GA-MANFIS model performance.

Organizational performance metrics	RMSE for testing data		Prediction improvement (%)	
	GA-ANFIS	GA-MANFIS	GA-ANFIS	GA-MANFIS
Overall organizational performance	0.16855	0.13784	-	22.28
Employee satisfaction	0.19885	0.18901	-	5.06
Customer satisfaction	0.17348	0.18078	4.04	-
Competitiveness	0.20569	0.24507	16.07	-
Quality of work	0.33917	0.32253	-	5.16
Safety performance	0.29598	0.27596	-	7.25
Effectiveness of planning	0.24667	0.19329	-	27.62

Overall, the GA-MANFIS model showed a better prediction performance than the corresponding GA-ANFIS model. The higher prediction accuracy obtained from GA-MANFIS in predicting multiple organizational performance metrics allows construction industry organizations to determine realistic organizational performance by analyzing their competencies. Furthermore, the multiple inputs and outputs can be narrowed down based on the context of the company for practical application. In addition, the capability of the GA-MANFIS to analyze multiple inputs, relate them to organizational performance metrics, and predict organizational performance using organizational competencies enhances construction practitioners' ability to identify potential competencies for performance improvement. Moreover, the GA-MANFIS model provides organizations and construction practitioners with insight into targeted areas for future investment and expansion strategies for improving organizational performance, which further helps them to make the best decisions. Thus, the proposed GA-MANFIS model has a great advantage over GA-ANFIS in that it can predict multiple organizational performance metrics simultaneously rather than developing an independent model for each output.

6.6 Chapter Summary

In this chapter, a hybrid GA-MANFIS model is developed to analyze organizational competencies and predict multiple performance metrics. The input-output data is cleaned and normalized for model development. GA-based FS is implemented to reduce the dimensionality of the original data to identify representative model input features i.e., organizational competencies. Furthermore, the FS helps to reduce model complexity and improve prediction performance of the model to obtain good results with high accuracy. The GA-MANFIS model was developed using 19 organizational competencies obtained from the GA-FS and the 7 organizational performance metrics. The proposed model was validated based on data collected from a construction company active in various industrial projects. The proposed GA-MANFIS model is able to simultaneously predict multiple organizational performance metrics with high accuracy. The results showed that the optimal model for predicting organizational performance metrics with minimum RMSE is the GA-

MANFIS model with 3 clusters, a population size of 50, and number of generations of 100. The proposed model showed a good performance with the highest accuracy in predicting multiple organizational performance metrics simultaneously. Sensitivity analysis was performed to identify the main parameters that affect model outputs. Accordingly, the size of population was found to have a significant impact on model outputs, especially when the model is developed and trained using limited data. Furthermore, results between GA-MANFIS and GA-ANFIS model outputs were compared, and the GA-MANFIS model performed better in predicting multiple organizational performance metrics simultaneously (Table 6.5) compared with individual, independent GA-ANFIS models for each performance metric.

This chapter makes three main contributions. First, it provides a novel methodology for developing GA-MANFIS models, which can model MIMO systems inherent in construction processes and practices. In addition, past studies focused mainly on MISO systems rather than modeling approaches that can handle multiple outputs. This chapter addresses the issue of handling multiple outputs common in real-world construction problems. Second, this chapter develops a hybrid GA-MANFIS for construction organizational competencies and performance that predicts multiple organizational performance metrics using organizational competencies, unlike the conceptual and regression models of previous construction research. Moreover, the GA-MANFIS model captures the overall aspects of multiple organizational competencies and establishes their complex and non-linear relationship to organizational performance. Third, this paper provides a GA-based FS approach that is not only vital for dimensionality reduction, but also for identifying organizational competencies influencing performance. Furthermore, the FS helps to reduce model complexity and improve model prediction performance to obtain good results with high accuracy. The proposed GA-MANFIS model enables construction organizations to identify and evaluate competencies that have significant impact on performance as well as predict multiple organizational performance metrics simultaneously. Moreover, the GA-MANFIS modeling approach does not require manual configuration; hence, it can serve as a reference for construction researchers for developing concise and accurate models that can predict multiple outputs for other CEM disciplines, such as risk, cost, and schedule management. Additionally, the proposed GA-MANFIS modeling methodology in this research is generalizable and can be adapted to different construction contexts and practical applications for different industry groups such as owners, consultants, and contractors. The next chapter presents summary of the work conducted in this research, research contributions, research limitations and recommendations for future research.

6.7 References

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Chapter 7 Conclusions and Recommendations[6]

7.1 Introduction

This chapter presents summary of the work conducted in this research and outlines the academic and industrial contributions. Moreover, limitations of this research and recommendations for future research are presented.

7.2 Research Summary

The construction industry is dynamic and complex that demands continuous quality, productivity, and performance improvement; making it challenging to achieve organizational success and superior performance. Organizational competencies have a significant influence on performance; hence, it is vital that construction organizations (e.g., owners, consultants, contractors, specialty or subcontractors) assess and enhance their competencies in order to improve performance. Despite availability of wide array of robust modeling techniques, most of competency and performance models are statistical and regression models that cannot capture subjective uncertainty, complex and nonlinear relationships inherent in construction. To address these limitations, fuzzy systems (fuzzy logic) and ANN have been integrated; hence, NFS which is a

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viable option to capture dynamic and complex nature of construction. Conventional NFS have limitations related to slow computational convergence and potential of being trapped in local minima that may lead to provide less accurate results and inadequate explanations for problems. Thus, efforts have been made to integrate NFS and evolutionary optimization techniques in construction to improve accuracy and generalization capability. However, most of conventional and hybrid NFS such as ANFIS fails to directly deal with MIMO systems due to their MISO structure. The main objective of this research is thus to develop a hybrid neuro-fuzzy system model (NFS) i.e., GA-MANFIS to analyze multiple organizational competencies, relate them to performance, and predict multiple organizational performance metrics simultaneously. The stages followed to achieve the objectives of this research are discussed in the following subsections.

7.2.1 The First Stage

In the first stage of this research, a systematic review and detailed content analysis was conducted to identify and categorize organizational competencies and performance metrics commonly used in the construction domain. Common organizational competencies and performance metrics in construction and their classification methods were examined as well as potential organizational competencies affecting organizational performance were identified, systematically categorized, and ranked. In order to achieve these objectives, a systematic review and detailed content analysis was conducted. A detailed list of organizational competencies and performance metrics were identified. A comprehensive and structured categorization method was established for organizational competencies and performance metrics based on the existing category names in the selected articles. Organizational competencies are grouped into two as functional competencies (how the organization operates and functions) and behavioral competencies (individual/organizational attributes). Furthermore, organizational performance metrics are organized into three categories as KPIs, KPOs, and PerMs. The comprehensive list and categorization of organizational competencies and performance metrics are verified and validated through a focus group.

A systematic review and detailed content analysis was conducted to investigate common NFS modeling methods used in the construction domain. Although efforts have been made to integrate NFS and evolutionary optimization techniques in construction to improve accuracy and generalization capability; the results of literature review also identified limitations of hybrid NFS in handling multiple outputs. For instance, most of conventional and hybrid NFS such as ANFIS fails to directly deal with MIMO systems due to their MISO structure. Furthermore, the results indicate a lack of effective method for modeling MIMO problems inherent in construction processes and practices.

7.2.2 The Second Stage

In the second stage of the research, a focus group was conducted to verify and validate organizational competencies and performance metrics identified and categorized in the first stage. The experts participated in the focus group reviewed the list and proposed additional competency and performance metrics they thought important at an organization level. The focus group allowed for the development of a comprehensive list of organizational competencies and performance metrics that not only considers the literature in construction and non-construction domains but also captures the opinions of construction experts practicing in the construction industry. The comprehensive list and categorization of organizational competencies and performance metrics validated through the focus group were used to design data collection survey forms.

7.2.3 The Third Stage

In the third stage of this research, a data collection protocol was prepared to describe the methodology and data collection process for developing the hybrid NFS model. First, data collection forms were developed based on the finalized list of organizational competencies and performance metrics based on the focus group results. Second, the data collection forms were pilot tested with a construction company prior to the data collection to ensure respondents understood the data collection forms as well as to check applicability of the evaluation, assessment, and measurement scales and techniques of the data collection forms. Third, data collection forms were then finalized incorporating the feedbacks from the pilot survey. As a result, two surveys – the senior management survey and the staff survey – were developed in order to collect organizational competencies influencing organizational performance. Finally, data collection was performed in a construction company actively involved in industrial construction projects. The surveys were administered online through Survey Monkey with the company's office and project personnel, including senior management, project managers, field supervisors, and foremen. Actual company performance metrics data were extracted and collected from relevant actual organizational/project documents at the organizational level (operational) and project level.

7.2.4 The Fourth Stage

In the fourth stage of this research, a hybrid NFS modeling methodology was developed to analyze organizational competencies, relate them to performance, and predict multiple organizational performance metrics. The proposed modeling methodology was applied to develop a hybrid GA-MANFIS model for organizational competencies and performance. The hybrid NFS model was developed in four phases: (i) data pre-processing encompassing data cleaning and normalization to resolve issues in the raw data such as outliers and missing values; (ii) performing GA-FS to reduce the dimensionality of data; (iii) development of the hybrid GA-MANFIS model to handle MIMO problems to predict multiple organizational performance metrics; and and GA-MANFIS model verification and validation.

Data preprocessing techniques such as data cleaning and normalization are implemented in order to eliminate outliers, missing values and noisy or bad data in order to facilitate modeling. Then, the original cleaned data which is normalized is then used to implement the GA-based FS to reduce the dimensionality of the data. Performing the GA-based FS encompasses FCM parameter optimization and GA-FS to reduce the dimensionality of original cleaned data to build a concise and efficient predictive model (i.e., help reduce computational time and improve model accuracy). In developing the hybrid GA-MANFS model, 19 organizational competencies obtained from the GA-FS and the seven organizational performance metrics identified for modeling purpose are used. To verify the GA-MANFIS model all mathematical equations and components of the model, such as MATLAB codes are checked for their correctness. Besides, running the model multiple times to check for the replicability of its results as well as use of tracing and plot graphs is conducted to track changes in the variables of the model. In addition, the hybrid GA-MANFIS models were validated by evaluating the performance of the GA-MANFIS model by comparing model outputs (i.e., predicted results) against the testing dataset using the fitness function (i.e., RMSE). Sensitivity analysis is also conducted to identify the main parameters of the GA-MANFIS model that affect the model outputs significantly. Finally, the results of the GA-MANFIS model is compared with a GA-ANFIS model outputs. The result revealed that the GA-MANFIS model showed a better prediction performance than the corresponding GA-ANFIS model.

7.3 Research Contributions

The academic and industrial contributions of this research relevant to academic researchers and construction industry practitioners, respectively are presented in the following subsections.

7.3.1 Academic Contributions

The main academic contributions of this research are summarised as follows:

1. *Providing a systematic and in-depth content analysis of published articles related to organizational competencies and performance metrics in construction, and a useful reference on a comprehensive hierarchical list of competencies and performance metrics for future analysis and modeling purposes.* This research addresses the lack of systematic review and content analysis of published articles related to organizational competencies and performance metrics in construction and established research areas in need of further examination. Common competency and performance identification and classification methods used in construction were identified. Also, potential competencies affecting organizational performance were identified, systematically categorized, and ranked. Moreover, a comprehensive competency and performance classification method applicable to different types of organizations in the construction industry has also been proposed. The proposed classification method of organizational competencies and performance metrics, which is verified through a focus group of construction experts, helps to avoid redundancy and ambiguity and contributes to the effectiveness of competency and performance identification process because the categories are detailed and comprehensive.
2. *Providing a systematic literature review and content analysis of NFS techniques in different construction applications and recommendations to researchers regarding suitable subsets*

of NFS techniques for solving different types of CEM problems. This research addresses the lack of systematic review and content analysis of published articles related to NFS modeling techniques in construction and established research areas in need of further examination. The most common NFS modeling techniques in construction in general and specifically for modeling construction organizational competencies and performance were identified. Also, commonly used NFS modeling approaches in construction were identified from the selected articles; categorized based on the nature of the NFs model learning algorithm; and provide recommendations to researchers regarding the suitability of NFS techniques in different CEM application categories.

3. *Providing an approach, using hybrid NFS modeling, that can handle multiple outputs in analyzing multiple organizational competencies as model inputs and predicting multiple organizational performance metrics with a good accuracy simultaneously.* This research addresses the lack of NFS modeling techniques that can handle MIMO systems inherent in construction. NFS modeling techniques commonly used in construction applications are identified and their suitability for modeling real-world construction problems was assessed. Despite its broad applicability to several fields of engineering, conventional NFS fails to directly deal with MIMO systems inherent in construction due to their MISO structure such as ANFIS. To address the lack of NFS that handle MIMO systems, a multi-output adaptive neuro-fuzzy inference system (MANFIS) is proposed. The core of the proposed MANFIS framework is a processing layer that contains a number of ANFIS modal blocks, which each corresponds to a single output. Thus, for K outputs, then there will be K numbers of ANFIS modal blocks in the MANFIS model. The proposed MANFIS model is trained using GA optimization to improve the performance of prediction accuracy. The resulting

hybrid GA-MANFIS model showed a good accuracy and better performance compared to a GA-ANFIS model.

4. *Contributing to the advancement of the state of the art in NFS modeling for organizational competencies and performance in construction by (a) providing a method for handling MIMO problems; (b) providing a structured and systematic GA-FS approach to reduce the dimensionality of data to develop a concise model with a better accuracy; and (c) implementing MF/parameter and model optimization to improve model performance.* The existing NFS modeling techniques in construction applications and specifically for organizational competency and performance modeling have limitations to handle multiple outputs due to their MISO configuration. This research addresses the lack of handling multiple outputs by developing a hybrid NFS modeling methodology that can analyze multiple-inputs and predict multiple-outputs. The proposed modeling methodology showed a good performance in predicting multiple organizational performance metrics simultaneously. The GA-FS methodology proposed in this research enables to represent large number of variables with high-dimensional data in the hybrid NFS model by selecting a representative feature subset of the original data and help reduce computational time and improve model accuracy. Moreover, this research addresses the lack of research on MF/parameter and model optimization by integrating NFS with evolutionary optimization techniques such as GA since they perform better in global search spaces to determine optimal solution.

7.3.2 Industrial Contribution

The main industrial contributions of this research are summarised as follows:

1. *Providing a useful reference of a comprehensive hierarchical competency and performance metrics for organizations in construction for future competency and performance identification, analysis, and modeling purposes.* This research provides industry practitioners with a detailed hierarchical list and classification of organizational competencies and performance metrics common in construction applicable to different types of organization in the construction industry such as owners, consultants, and contractors. The detailed list and categorization of organizational competencies are verified and validated through a focus group of construction practitioners. Thus, the detailed and comprehensive list of identified organizational competencies and performance metrics and the proposed classification method contributes to the effectiveness organizations in the construction industry in identifying and analyzing their competencies to improve their performance.

2. *Provide an approach to identify organizational competencies that have a significant impact on organizational performance and determine competencies that need improvement that help to increase performance.* This research provides a data analysis methodology to identify critical competencies influencing organizational performance as well as competencies with a high potential for organizational performance improvement. Moreover, a comparative analysis of perceptions of different survey respondent groups on critical competencies influencing performance was done. Competencies that showed statistically significant differences of perception among survey respondent groups regarding the impact or influence of competencies on performance were identified. Thus, incorporating construction practitioners' opinions through surveys ensures that critical competencies influencing performance are identified for further analysis and modeling.

3. *Providing a modeling and analysis approach that allows construction industry practitioners to assess organizational competencies and predict organizational performance.* This research provides an analysis approach to determine relationship between organizational competencies and organizational performance using correlation analysis. The findings indicate that, an increase in organizational competencies (functional and behavioral competencies) enable improvement of organizational performance. Thus, it is important that company policies be directed to place a greater focus on enhancing competencies for which the weakest relationship was observed in order to further improve overall organizational performance.

4. *Providing a hybrid NFS modeling approach to understand the impact of organizational competencies on performance and predict multiple organizational performance metrics.* Unlike the conventional NFS methods, the proposed hybrid NFS modeling approach i.e., GA-MANFIS allows industry practitioners to predict multiple organizational performance metrics simultaneously with good accuracy. In addition, the capability of the proposed modeling methodology to analyze multiple inputs, relate them to organizational performance metrics, and predicting organizational performance using organizational competencies provides construction practitioners with the ability to identify potential competencies for performance improvement. Moreover, the proposed model provides organizations as well as construction practitioners with insight into targeted areas for future investment and improvement strategies to increase organizational performance.

7.4 Research Limitations and Recommendations for Future Research

The limitations of this research and recommendations for future research are discussed in the following subsections.

7.4.1 Content Analysis on Identification and Categorization of Organizational Competencies and Performance Metrics in Construction

The systematic review and content analysis carried out to identify and categorize organizational competencies and performance metrics in construction is more general and not context specific. Using the research methodology adopted for the content analysis, future research should focus on the identification of common organizational competencies and performance metrics and their respective categorization methods for different contexts based on type of organization (e.g., owner, consultant, construction management, general contractor, specialty/subcontractor); size of firm/organization (e.g., small, medium, large); ownership type of organization (e.g., public/government owned, privately owned, employee owned, publicly traded); construction industry subsector type (e.g., building, commercial, industrial); and contracting strategies or delivery methods of projects the organization is involved in (e.g., design, design build, construction EPC (engineering, procurement, and construction), EPCM (engineering, procurement, and construction management), PPP (public-private partnership)).

7.4.2 Focus Group Verification and Validation of Organizational Competencies and Performance Metrics

Focus groups usually consist of six to eight preselected participants who have similar backgrounds or shared experiences related to the research topic being studied (Hennink 2014; Liamputtong 2011). The relatively small number of participants in a focus group may affect the representativeness of the study results. However, a large sample size for a focus group is not necessarily beneficial, as it does not facilitate sharing deep and intimate experiences and insights among participants (Millward 2006). For this research, only a single focus group with 13 participants was conducted due to challenges of assembling highly experienced experts (e.g., continued commitment to participate in multiple focus groups). The number of focus group participants (i.e., n = 13) was sufficient for the focus group discussion; however, this number of participants may have been a limitation when calculating the *RII* and -ranking competency and performance metrics. Established credible data collection and analysis procedures were followed to ensure the validity and reliability of the results: (1) purposive sampling was adopted to ensure participants were qualified and had the required experience; (2) multiple sources of evidence, such as participants' written suggestions in the focus group survey and notes taken during the focus group discussion, were collected to ensure data reliability; and (3) the focus group discussion was summarized and reproduced in the results section of chapter 3 to enhance the reliability of the results. The extensive and detailed content analysis conducted prior to the focus group as well as the participants' expertise in evaluating and verifying the list of organizational competency and performance measures was helpful for generalizing the results.

The ranking order of competency categories using the mean *RII* may have been impacted by the number of competencies in each category and the focus group size. Furthermore, the importance of each competency and/or performance measure may be dependent on the organizational and operational context of the company. Therefore, considering the broad nature of the construction industry, the ranking of competency and/or performance measures was done based on the context of the companies represented in the focus group. Therefore, future research can consider multiple focus groups and alternative methods, such as the Delphi method, to obtain a more generalizable results.

7.4.3 Comparative Analysis of Organizational Competencies Influencing Organizational Performance

The data used for the analysis is collected from a single construction company; hence, the result cannot be generalized to the wider construction industry. Furthermore, the comparative analysis conducted on the three survey respondent groups (i.e., senior management, middle and lower management, office and project site staff) has limitations due to lack of adequate data. Although senior management in organizations are few, the relatively small number of SM survey respondents is a limitation that may affect the result. In order to generalize the results, additional data should be collected to capture the perspectives of SM as well as MLM and OPS from multiple organizations and further analysis needs to be performed. Thus, future research should focus in collecting data from multiple organizations from various construction industry subsectors for different contexts described in section 7.4.1.

7.4.4 Improvement of the GA-FS Method

In this research, a GA-FS method was employed to reduce dimensionality of input data attributes and help reduce computational time and improve model accuracy. It is important to investigate FS and instance selection (IS), as well as dimensionality reduction techniques such as principal component analysis (PCA), to improve the accuracy and generalization capability of the NFS model for construction application. For example, Ahmad and Pedrycz (2012) integrated FS and IS in the construction of fuzzy models and applying it simultaneously to the initial dataset, in order to obtain a suitable subset of feature and data to construct the parameters for the fuzzy model.

However, research in the area of construction engineering and management is characterized by high dimensionality of features (parameters or variables) compared to their associated data instances (Saitta et al. 2010). Due to limitation of the data instance (i.e., 62) only FS is performed in this research. Thus, future research should focus on to explore and develop an approach to integrate feature selection and data instance selection for more accurate and interpretable NFS for future modeling efforts. Additionally, dimensionality reduction techniques such as feature selection, feature extraction, principal component analysis, factor analysis, and/or subjective judgement should be explored to obtain fewer critical input (competencies)-output (performance metrics) for practical applications by different industry stakeholders, such as owners, consultants, and contractors based on the context of the company for which the model is developed.

7.4.5 Further Improvement of Hybrid NFS Model

The major challenge of construction engineering and management research is the presence of constraints on getting adequate data (Saitta et al. 2010). The hybrid NFS model developed in this research is only capable of predicting multiple organizational performance metrics based on the limited data obtained from a single context. Future research should strive to collect data from multiple organizations for varying contexts. Incorporating different contexts in the proposed hybrid NFS model helps the model to be flexible for varying contexts. Thus, future research should focus on to incorporate different contexts to expand the hybrid NFS model. Furthermore, future research should also explore the integration of evolutionary optimization algorithms and deep learning techniques, such as extreme learning machine, in order to enhance and speed up the model training and optimization process. Due to the limited amount of data available for modeling, a ratio of 80/20 of testing to training data was used for validation. Thus, future research should consider *k*-fold cross-validation to compare the prediction performance of different models, particularly those developed using small data sets.

Organizational competencies and performance metrics used for developing the hybrid NFS are considered to be independent without any interaction. Given the multi-level nature of organizational competencies, competencies in different levels (e.g., project vs organization-level for functional competencies, individual vs management for behavioral competencies) may have an impact on two or more performance metrics at the same time (i.e., concurrent impact). Moreover, the cumulative impact of interrelated and interacting competencies on two or more organizational performance metrics is different than the sum of the individual impacts of independent competencies on a specific organizational performance metric. Thus, this research should be extended in the future to develop a hybrid NFS model to determine the concurrent and cumulative impact of competencies on two or more organizational performance metrics. Furthermore, future research can explore different modeling approaches to integrate models at different levels (e.g., project team/crew, project, and organizational levels), such as fuzzy system dynamics (FSD) and fuzzy agent-based modeling (FABM), to effectively model concurrent and cumulative effects of competencies on two or more organizational performance metrics and on overall organizational performance. Additionally, future research can explore the integration of competency-performance models at different levels (e.g., project team/crew, project, and organizational).

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Appendices

Appendix A. Selected Articles for the Content Analysis

No.	Journal Name	Author(s)	Year	Title of the article
1	AC	Chao, L., and Hsiao, C.	2012	Fuzzy model for predicting project performance based on procurement experiences
2	AC	Cheung, S. O., Suen, H. C. H., and Cheung K. K. W.	2004	PPMS: A web-based construction project performance monitoring system
3	AC	Omar, M. N. and Fayek, A. R.	2016	Modeling and evaluating construction project competencies and their relationship to project performance
4	AC	Succar, B., Sher, W., and Williams, A.	2013	An integrated approach to BIM competency assessment, acquisition and application
5	AC	Uhm, M., Lee, G., and Jeon, B.	2017	An analysis of BIM jobs and competencies based on the use of terms in the industry
6	CiI	Boucher, X., Bonjour, E., and Grabot, B.	2007	Formalization and use of competencies for industrial performance optimization: A survey
7	CiI	Harzallah, M., and Vernadat, F.	2002	IT-based competency modeling and management: From theory to practice in enterprise engineering and operations
8	CiI	Nudurupati, S., Arshad, N., and Turner, T.	2007	Performance measurement in the construction industry: An action case investigating manufacturing methodologies
9	CiI	Rauffet, P., Da Cunha, C., and Bernard, A.	2012	Conceptual model and IT system for organizational capability management
10	CiI	Worley, J. H., Chatha, K. A., Weston, R. H., Aguirre, O., and Grabot, B.	2005	Implementation and optimization of ERP systems: A better integration of processes, roles, knowledge and user competencies
11	CJCE	Esmaili, D., and El-Diraby, T. E.	2017	Organizational competency in urban water infrastructure asset management
12	CJCE	Hanna, A. S., Iskandar, K. A., Lotfallah, W., Ibrahim, M. W., and Russell, J. S.	2018	A data-driven approach for identifying project manager competency weights
13	CJCE	Rankin, J., Fayek, A. R., Meade, G., Haas, C., and Manseau, A.	2008	Initial metrics and pilot program results for measuring the performance of Canadian construction industry
14	CME	Ahadzie, D. K., Proverbs, D. G., Olomolaiye, P. O., and Ankrah, N.	2009	Towards developing competency-based measures for project managers in mass house building projects in developing countries
15	CME	Arditi, D., Gluch, P., and Holmdahl, M.	2013	Managerial competencies of female and male managers in the Swedish construction industry
16	CME	Brown, A. D., and Phua, F. T. T.	2011	Subjectively construed identities and discourse: Towards a research agenda for construction management
17	CME	Chan, T. K.	2009	Measuring performance of the Malaysian construction industry
18	CME	Cheah, C. Y. J., Kang, J., and Chew, D. A. S.	2007	Strategic analysis of large local construction firms in China
19	CME	Dainty, A. R. J., Cheng, M., and Moore, D. R.	2003	Redefining performance measures for construction project managers: An empirical evaluation
20	CME	Dainty, A. R. J., Cheng, M., and Moore, D. R.	2004	A competency-based performance model for construction project managers
21	CME	Egbu, C. O.	1999	Skills, knowledge and competencies for managing construction refurbishment works
22	CME	Kim, A., and Arditi, D.	2010	Performance of minority firms providing construction management services in the US transportation sector

No.	Journal Name	Author(s)	Year	Title of the article
23	CME	Konanahalli, A., and Oyedele L. O.	2016	Emotional intelligence and British expatriates' cross-cultural adjustment in international construction projects
24	CME	Luu, T., Kim, S., Cao, H., and Park, Y.	2008	Performance measurement of construction firms in developing countries
25	CME	Nkado, R., and Meyer, T.	2001	Competencies of professional quantity surveyors: A South African perspective
26	CME	Ruddock, L., and Ruddock, S.	2009	Reassessing productivity in the construction sector to reflect hidden innovation and the knowledge economy
27	CME	Rwelamila, P. M. D.	2007	Project management competence in public sector infrastructure organisations
28	CME	Santoso, J., and Loosemore, M.	2013	Expatriate management in Australian multinational enterprises
29	CME	Xia, B., Chan, A. P. C., and Yeung, J. F.Y.	2009	Identification of key competences of design-builders in the construction market of the People's Republic of China (PRC)
30	CME	Yasamis, F., Arditi, D., and Mohammadi, J.	2002	Assessing contractor quality performance
31	DS	Cleveland, G., Schroeder, R. G., and Anderson, J. C.	1989	A theory of production competence
32	DS	Hitt, M. A., and Ireland, R. D.	1985	Corporate distinctive competence and performance: Effects of perceived environmental uncertainty (PEU), size, and technology
33	DS	Stratman, J. K., and Roth, A. V.	2005	Enterprise resource planning (ERP) competence constructs: Ibo-stage multi-item scale development and validation
34	DS	Vickery, S. K., Droge, C., and Markland, R. E.	1993	Production competence and business strategy: Do they affect business performance?
35	DS	Vickery, S. K.	1991	A theory of production competence revised
36	EMJ	Bartel-Radic, A., and Giannelloni, J.	2017	A renewed perspective on the measurement of cross-cultural competence: An approach through personality traits and cross-cultural knowledge
37	EMJ	Harvey, M., and Lusch, R.	1997	Protecting the core competencies of a company: Intangible asset security
38	EMJ	Lokshin, B., Van Gils, A., and Bauer, E.	2009	Crafting firm competencies to improve innovative performance
39	EMJ	Mothe, C., and Quelin, B.	2000	Creating competencies through collaboration: The case of EUREKA R&D Consortia
40	ESA	Bohlouli, M., Mittas, N., Kakarontzas, G., Theodosiou, T., Angelis, L., and Fathi, M.	2017	Competence assessment as an expert system for human resource management: A mathematical approach
41	ESA	Chin, K., Punb, K., and Lau, H.	2003	Development of a knowledge-based self-assessment system for measuring organizational performance
42	ESA	Horta, I. M., and Camanho, A. S.	2014	Competitive positioning and performance assessment in the construction industry
43	ESA	Hsu, I.	2008	Knowledge sharing practices as a facilitating factor for improving organizational performance through human capital: A preliminary test
44	ESA	Lee, Y.	2010	Exploring high-performers' required competencies
45	ESA	Sun, C.	2010	A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods
46	ESA	Wu, W.	2009	Exploring core competencies for R&D technical professionals

No.	Journal Name	Author(s)	Year	Title of the article
47	ESA	Wu, W., and Lee, Y.	2007	Developing global managers' competencies using the fuzzy DEMATEL method
48	HRMR	Cohen, D. J.	2015	HR past, present and future: A call for consistent practices and a focus on competencies
49	HRMR	Riggio, R. E., and Lee, J.	2007	Emotional and interpersonal competencies and leader development
50	HRMR	Russell, Z. A., Steffensen, D. S., Ellen III, B. P., Zhang, L., Bishoff, J. D., and Ferris, G. R.	2018	High performance work practice implementation and employee impressions of line manager leadership
51	HRMR	Sanchez, J. I., and Levine, E. L.	2009	What is (or should be) the difference between competency modeling and traditional job analysis?
52	IJCRB	Anari, R. Y., and Rezaei, S.	2013	Supply chain management competence and performance: An entrepreneurial approach in Iranian IT SMEs
53	IJCRB	Gholipur, R. A., Mahmoodi, S. M., Jandaghi, G., and Fardmanesh, H.	2012	Presentation model of managerial competency approach in management development
54	IJCRB	Janjua, S. Y., Naeem, M. A., and Kayani, F. N.	2012	The competence classification framework a classification model for employee development
55	IJPE	Khanchanapong, T., Prajogo, D., Sohal, A. S., Cooper, B. K., Yeung, A. C. L., and Cheng, T. C. E.	2014	The unique and complementary effects of manufacturing technologies and lean practices on manufacturing operational performance
56	IJPE	Barnes, J. and Liao, Y.	2012	The effect of individual, network, and collaborative competencies on the supply chain management system
57	IJPE	Chavez, R., Yu, W., Jacobs, M. A., and Feng, M.	2017	Manufacturing capability and organizational performance: The role of entrepreneurial orientation
58	IJPE	Horta, I. M., Camanho, A. S., and Da Costa, J. M.	2012	Performance assessment of construction companies: A study of factors promoting financial soundness and innovation in the industry
59	IJPE	Yang, J.	2010	The knowledge management strategy and its effect on firm performance: A contingency analysis
60	IJPM	Adler, T. R., Pittz, T. G., and Meredith, J.	2016	An analysis of risk sharing in strategic R&D and new product development projects
61	IJPM	Ahadzie, D. K., Proverbs, D. G., and Olomolaiye, P.	2008	Towards developing competency-based measures for construction project managers: Should contextual behaviors be distinguished from task behaviors?
62	IJPM	Ahadzie, D. K., Proverbs, D. G., and Sarkodie-Poku, I.	2014	Competencies required of project managers at the design phase of mass house building projects
63	IJPM	Crawford, L., and Nahmias, A. H.	2010	Competencies for managing change
64	IJPM	Edum-Fotwe, F. T., and McCaffer, R.	2000	Developing project management competency: Perspectives from the construction industry
65	IJPM	Ekrot, B., Kock, A., and Gemünden, H. G.	2016	Retaining project management competence – Antecedents and consequences
66	IJPM	Engelbrecht, J., Johnston, K. A., and Hooper V.	2017	The influence of business managers' IT competence on IT project success
67	IJPM	Medina, R., and Medina, A.	2014	The project manager and the organization's long-term competence goal
68	IJPM	Palacios-Marqués, D., Cortés-Grao, R., and Carral, C. L.	2013	Outstanding knowledge competences and web 2.0 practices for developing successful e-learning project management
69	IJPM	Shao, J.	2017	The moderating effect of program context on the relationship between program managers' leadership competences and program success

No.	Journal Name	Author(s)	Year	Title of the article
70	IJHRM	Apospori, E., Nikandrou, I., Brewster, C. and Papalexandris, N.	2008	HRM and organizational performance in northern and southern Europe
71	IJHRM	Carstens, J. G., and De Kock, F. S.	2017	Firm level diversity management competencies: Development and initial validation of a measure
72	IJHRM	Chao M., and Shih, C.	2016	Customer service-focused HRM systems and firm performance: Evidence from the service industry in Taiwan
73	IJHRM	De Vos, A., De Hauw, S., and Willemse, I.	2015	An integrative model for competency development in organizations: the Flemish case
74	IJHRM	Díaz-Fernández, M., López-Cabrales, A., and Valle-Cabrera, R.	2013	In search of demanded competencies: Designing superior compensation systems
75	IJHRM	Graf, A.	2004	Screening and training inter-cultural competencies: Evaluating the impact of national culture on inter-cultural competencies
76	IJHRM	Gray, L.	1999	New Zealand HRD practitioner competencies: Application of the ASTD competency model
77	IJHRM	Lo, K., Macky, K., and Pio, E.	2015	The HR competency requirements for strategic and functional HR practitioners
78	IJHRM	Long, C. S., and Ismail, W. K. W.	2011	An analysis of the relationship between HR professionals' competencies and firms' performance in Malaysia
79	IJHRM	Long, C. S., Ismail, W. K. W., and Amin, S. M.	2013	The role of change agent as mediator in the relationship between HR competencies and organizational performance
80	IJHRM	Wickramasinghe, V., and De Zoyza, N.	2011	Managerial competency requirements that enhance organisational competences: A study of a Sri Lankan telecom organisation
81	IJHRM	Wickramasinghe, V., and De Zoyza, N.	2009	An assessment of managerial competency needs: Empirical evidence from a Sri Lankan telecommunication service provider
82	JCEM	Deng, F., and Smyth, H.	2014	Nature of firm performance in construction
83	JCEM	Deng, F., and Smyth, H.	2013	Contingency-based approach to firm performance in construction: Critical review of empirical research
84	JCEM	Guo, B. H. W., Yiu, T. W., González, V. A., and Goh, Y. M.	2016	Using a pressure-state-practice model to develop safety leading indicators for construction projects
85	JCEM	Hanna, A. S., Ibrahim, M. W., Lotfallah, W., Iskandar, K. A., and Russell, J. S.	2016	Modeling project manager competency: An integrated mathematical approach
86	JCEM	Horta, I. M., Camanho, A. S., and Da Costa, J. M.	2010	Performance assessment of construction companies integrating key performance indicators and data envelopment analysis
87	JCEM	Jin, Z., Deng, F., Li, H., and Skitmore, M.	2013	Practical framework for measuring performance of international construction firms
88	JCEM	Karakhan, A. A., Rajendran, S., Gambatese, J., and Nnaji, C.	2018	Measuring and evaluating safety maturity of construction contractors: Multicriteria decision-making approach
89	JCEM	Kim, A., and Arditi, D.	2010	Performance of MBE/DBE/WBE construction firms in transportation projects
90	JCEM	Pereira, E., Han, S., AbouRizk, S. and Hermann, U.	2017	Empirical testing for use of safety related measures at the organizational level to assess and control the on-site risk level
91	JETM	Akgun, A. E., Keskin, H., and Byrne, J.	2009	Organizational emotional capability, product and process innovation, and firm performance: An empirical analysis

No.	Journal Name	Author(s)	Year	Title of the article
92	JETM	Bolivar-Ramos, M. T., Garcia-Morales, V. J., and Garcia-Sanchez, E.	2012	Technological distinctive competencies and organizational learning: Effects on organizational innovation to improve firm performance
93	JETM	Chaudhuri, A., and Boer, H.	2016	The impact of product-process complexity and new product development order winners on new product development performance: The mediating role of collaborative competence
94	JETM	Fowler, S. W., King, A. W., Marsh, S. J., and Victor, B.	2000	Beyond products: new strategic imperatives for developing competencies in dynamic environments
95	JETM	Hwang, D., Yang, M. G., and Hong, P.	2015	Mediating effect of IT-enabled capabilities on competitive performance outcomes: An empirical investigation of ERP implementation
96	JETM	Kilic, K., Ulusoy, G., Gunday, G., and Alpkan, L.	2015	Innovativeness, operations priorities and corporate performance: An analysis based on a taxonomy of innovativeness
97	JETM	Wang, Y., Lo, H., and Yang, Y.	2004	The constituents of core competencies and firm performance: Evidence from high-technology firms in china
98	JME	Dainty, A. R. J., Cheng, M., and Moore, D. R.	2005	Competency-based model for predicting construction project managers' performance
99	JME	Isik, Z., Arditi, D., Dikmen, I. and Birgonul, M. T.	2010	Impact of resources and strategies on construction company performance
100	JME	Lee, C., Chong, H., Liao, P., and Wang, X.	2017	Critical review of social network analysis applications in complex project management
101	JME	Lee, S., Yu, J., and Jeong, D.	2014	BIM acceptance model in construction organizations
102	JME	Rojas, E. M.	2013	Identifying, recruiting, and retaining quality field supervisors and project managers in the electrical construction industry
103	JME	Tripathi, K. K., and Jha, K. N.	2017	Determining success factors for a construction organization: A structural equation modeling approach
104	JME	Yu, I., Kim, K., Jung, Y., and Chin, S.	2007	Comparable performance measurement system for construction companies
105	SMJ	Arrfelt, M., Wiseman, R. M., McNamara, R., and Hult, G. T. M.	2015	Examining a key corporate role: the influence of capital allocation competency on business unit performance
106	SMJ	Hitt, M. A., and Ireland, R. D.	1985	Corporate distinctive competence, strategy, industry and performance
107	SMJ	King, A. W., and Zeithaml, C. P.	2001	Competencies and firm performance: Examining the causal ambiguity paradox
108	SMJ	Tippins, M. J., and Sohi, R. S.	2003	IT competency and firm performance: Is organizational learning a missing link?
109	AACE IT	Hollmann, J. K. and Elliott, B. G.	2006	Core competencies, expectations and career path for an estimating professional
110	ACAJ	Zingheim, P. K.; Ledford Jr., G. L., and Schuster, J. R.	1996	Competencies and competency models: Does one size fit all?
111	BRIS JST	Salajeghe, S., Sayadi, S., and Mirkamali, K. S.	2014	The relationship between competencies of project managers and effectiveness in project management: A competency model
112	CI	Murphy, M. E.	2014	Implementing innovation: A stakeholder competency-based approach for BIM
113	IAMA C	Brophy, M., and Kiely, T.	2001	Competencies; A new sector; Developing a competency model for three star hotels

No.	Journal Name	Author(s)	Year	Title of the article
114	IBERJ	Rambe, P., and Makhalemele, N.	2015	Relationship between managerial competencies of owners/managers of emerging technology firms and business performance: A conceptual framework of internet cafés performance in South Africa
115	ICCI	Mahmood, A., Hamidaddin, A., and Shafiei, M.	2006	What competencies do project managers need?
116	IJAEC	Omar, M. N. and Fayek, A. R.	2016 b	Organizational Competencies and Project Performance Tool (OCPPT©): Evaluating construction project competencies and performance
117	IRBRP	Shirazi, A., and Mortazavi, S.	2009	Effective management performance: A competency-based perspective
118	JATM	Liang, C., Lin, Y., and Huang, H.	2013	Effect of core competence on organizational performance in an airport shopping center
119	JBI	Edgar, W. B., and Lockwood, C. A.	2008	Organizational competencies: Clarifying the construct
120	JCiEM	Radujkovic, M., Vukomanović, M., and Dunović, I. B.	2010	Application of key performance indicators in south-eastern European construction
121	JKSU-ES	Ali, H. A. E. M.; Al-Sulaihi, I. A., and Al-Gahtani, K. S.	2013	Indicators for measuring performance of building construction companies in Kingdom of Saudi Arabia
122	LODJ	Woodruffe, C.	1993	What is meant by a competency?
123	OS	Grant, R. M.	1996	Prospering in dynamically-competitive environments: Organizational capability as knowledge integration
124	P	Boyatzis, R. E.	2006	Using tipping points of emotional intelligence and cognitive competencies to predict financial performance of leaders
125	V	Mukhopadhyay, K., Sil, J., and Banerjea, N. R.	2011	A competency based management system for sustainable development by innovative organizations: A proposal of method and tool

Note: *AC = Automation in Construction, CJCE = Canadian Journal of Civil Engineering, CiI = Computers in Industry, CME = Construction Management and Economics, DS = Decision Sciences, ESA = Expert Systems with Applications, HRMR = Human Resource Management Review, IJCRB = Interdisciplinary Journal of Contemporary Research in Business, IJPM = International Journal of Project Management, IJHRM = International Journal of Human Resource Management, IJPE = International Journal of Production Economics, JCEM = Journal of Construction Engineering and Management, JETM = Journal of Engineering and Technology Management, JME = Journal of Management in Engineering, SMJ = Strategic Management Journal, AACE IT = Association for the Advancement of Cost Engineering International Transactions, ACAJ = American Compensation Association Journal, BRIS JST = BRIS Journal of Science and Technology (MAGNT Research Report), CI = Construction Innovation, EMJ = European Management Journal, IAMAC = The Irish Academy of Management Annual Conference, IJCRB = Interdisciplinary Journal of Contemporary Research in Business, IBERJ = International Business and Economics Research Journal, ICCI = International Conference on Construction Industry, IJAEC = International Journal of Architecture, Engineering and Construction, IRBRP = International Review of Business Research Papers, JATM = Journal of Air Transport Management, JBI = Journal of Business Inquiry, JCiEM = Journal of Civil Engineering and Management, JKSU-ES = Journal of King Saud University – Engineering Sciences, LODJ = Leadership & Organization Development Journal, OS = Organization Science, P = Psicothema, V = Vision.*

Appendix B. *RII* and Ranking of Organizational Competencies and Performance based on Focus Group Survey Analysis

Appendix B.1. *RII* and Ranking of Functional Competencies

No.	Competency category and competencies	*RII*	Rank in category	Overall rank	No.	Competency category and competencies	*RII*	Rank in category	Overall rank
	General Administration Competencies				28	Management information systems/technology	0.850	3	29
1	Staff development/training	0.831	1	35	29	New technology/product development	0.785	4	48
2	Results orientation	0.831	1	35		**Project Management Competencies**			
3	Goal orientation	0.800	3	46	30	Safety, health, security, and environment	0.954	1	2
4	Human resources/personnel	0.738	4	53	31	Quality management	0.923	2	6
5	Managing and support of diversity	0.723	5	55	32	Schedule (time) management	0.923	2	6
	Technical Competencies				33	Scope management	0.923	2	6
6	Quality of work	0.969	1	1	34	Change management	0.908	5	10
7	Technical/job knowledge	0.954	2	2	35	Managing performance	0.908	5	10
8	Commitment to safety	0.938	3	4	36	Cost management	0.892	7	15
9	Planning and organizing (tasks/activities)	0.908	4	10	37	Commissioning and start-up	0.892	7	15
10	Strategic planning and management	0.818	5	43	38	Project monitoring & controlling	0.892	7	15
11	Attention to detail (work processes and procedures)	0.800	6	46	39	Project resource management	0.877	10	19
12	Business acumen/ business management skills	0.785	7	48	40	Risk management	0.862	11	25
13	Market management	0.700	8	57	41	Design development	0.862	11	25
14	Finance management	0.650	9	58	42	Integration management	0.862	11	25
	Cross-Functional Competencies				43	Project materials management	0.846	14	31
15	Cooperation and coordination	0.933	1	5	44	Stakeholder management	0.831	15	35

No.	Competency category and competencies	*RII*	Rank in category	Overall rank	No.	Competency category and competencies	*RII*	Rank in category	Overall rank
16	Stakeholder focus	0.877	2	19	45	Contract administration	0.831	15	35
17	Communication management	0.867	3	24	46	Project communications management	0.831	15	35
18	Delegation	0.831	4	35	47	Environmental management	0.831	15	35
19	Public and government relations	0.754	5	51	48	Team building	0.815	19	44
	Production/Operations Competencies				49	Procurement management	0.815	19	44
20	Construction technology/ integration management	0.908	1	10	50	Project human resource management	0.769	21	50
21	Operations and maintenance	0.908	1	10	51	Program management	0.754	22	51
22	Process engineering management	0.862	3	25	52	Conflict management	0.738	23	53
23	Construction, production, and manufacturing	0.850	4	29	53	Commitment to sustainability	0.723	24	55
24	Materials management	0.846	5	31		**Supervisory/Managerial competencies**			
25	Product engineering	0.831	6	35	54	Values and ethics	0.923	1	6
	Construction and Engineering Research and Development Competencies				55	Engagement	0.877	2	19
26	Business, legal, and public policy	0.883	1	18	56	Management effectiveness/excellence	0.877	2	19
27	Construction law and regulation	0.877	2	19	57	Resource management	0.846	4	31
					58	Strategic thinking	0.846	4	31

Appendix B.2. ***RII* and Ranking of Behavioral Competencies**

No.	Competency category and competencies	*RII*	Rank in category	Overall rank	No.	Competency category and competencies	*RII*	Rank in category	Overall rank
	Organizational Attributes				20	Planning and organizing	0.892	3	14
1	Ability to build trust	0.933	1	5	21	Results orientation	0.877	4	15
2	Competitiveness	0.917	2	8	22	Responsiveness	0.877	4	15
3	Adaptability/flexibility	0.908	3	9	23	Influence	0.846	6	24
4	Achievement drive	0.908	3	9	24	Communication	0.846	6	24
5	Innovation	0.862	5	20	25	Incisiveness	0.831	8	32
6	Organizational awareness, culture, and values	0.862	5	20		**Individual/Personal Competencies**			
7	Risk-taking	0.785	7	38	27	Reliability/dependability	0.938	1	3
	Top Management Competencies					Teamwork	0.908	2	9
8	Leadership	0.969	1	1	29	Ethics	0.908	2	9
9	Strategic thinking	0.954	2	2	30	Initiative	0.877	4	15
10	Judgement	0.846	3	24	31	Commitment	0.877	4	15
11	Analytical ability	0.831	4	32	32	Effectiveness	0.877	4	15
	Middle Management Competencies					Self-regulation/control	0.862	7	20
12	Interpersonal skills	0.923	1	6	34	Motivation	0.862	7	20
13	Decision-making	0.923	1	6	35	Resourcefulness	0.846	9	24
14	Consultation	0.846	3	24	36	Perseverance	0.840	10	31
15	Negotiation	0.846	3	24	37	Attention to detail	0.831	11	32
16	Reasoning	0.846	3	24	38	Professionalism	0.831	11	32
17	Conflict and crisis resolution/issue management	0.831	6	32	39	Cognitive skills	0.815	13	37
18	Assertiveness	0.767	7	40	40	Self-confidence	0.769	14	39
	First-line Management Competencies					Creativity	0.754	41	41
19	Problem-solving	0.938	1	3	42	Sales mindset/selling skills	0.708	16	42
20	Integrity/high standards	0.908	2	9	43	Enthusiasm	0.692	17	43

Appendix B.3. *RII* and Ranking of Organizational Performance Metrics

No.	Performance measure category and metrics	*RII*	Rank in category	Overall rank	No.	Performance measure category and metrics	*RII*	Rank in category	Overall rank
	KPIs					**Growth**			
	Cash flow				23	Revenue growth	0.862	1	17
1	Cash flow	0.933	1	6	24	Sales growth	0.785	2	29
	Quality of work				25	Volume of works growth	0.723	3	38
2	Rework factor,	0.892	1	13		**Business efficiency**			
3	Prevention, appraisal, and failure (PAF) model	0.846	2	21	26	Net profit margin	0.846	1	21
	Market Share				27	Efficiency ratio	0.767	2	34
4	Market share	0.800	1	28		**Effectiveness of planning**			
5	Market returns	0.708	2	40	28	Cost predictability	0.933	1	6
	Safety				29	Time predictability	0.900	2	12
6	Incident rate	0.938	1	2	30	Change cost factor	0.867	3	15
7	Time lost	0.938	1	2	31	Cost growth/increase	0.867	3	15
8	Safety performance	0.917	3	9	32	Time growth/increase	0.833	5	25
9	Accident frequency rate	0.862	4	17		**PerMs**			
10	Accident cost	0.817	5	27		**Internal customer satisfaction**			
	Financial stability				33	Employee satisfaction	0.908	1	10
11	Debt ratio	0.769	1	31	34	Employee turnover rate	0.846	2	21
12	Liquidity	0.754	2	35	35	Average remuneration per employee	0.769	3	31
	KPOs				36	Profit per employee	0.738	4	37
	Profitability				37	Turnover/revenue per employee	0.723	5	38
13	Profitability	0.967	1	1		**External customer satisfaction**			
14	Return on assets	0.938	2	2	38	Customer satisfaction	0.877	1	14
15	Return on investment	0.923	3	8	39	Customer retention/loyalty	0.846	2	21
16	Net income	0.908	4	10	40	Percentage of repeat customers	0.785	3	29
17	Return on capital	0.862	5	17	41	Number of complaints	0.769	4	31
18	Return on equity	0.862	5	17		**Competitiveness**			
19	Economic value added	0.831	7	26	42	Company image/reputation	0.938	1	2
20	Return on sales	0.750	8	36	43	Competitive advantage	0.908	2	10
21	Financial autonomy	0.700	9	41	44	Market advantage	0.877	3	14
22	Hanging invoice	0.677	10	42					

Appendix C. List and Definitions of Organizational Competency and Performance Metrics Used for Data Collection

Appendix C.1. List and Definitions of Organizational Functional Competencies

No.	Functional competency	Competency definition
1	***General administration competencies***	The planning, acquisition, and management of personnel and the use of management objectives and participative decision-making to ensure due diligence in proper management practices.
1.1	Staff development/training	Address knowledge gaps by providing training, continuous learning, and career and professional development
1.2	Goal orientation	Set short-term and long-term goals and strive to achieve them through effective resources and utilization
1.3	Human resource (personnel) management	Recruitment, retention, reward, motivation, welfare, health, and safety to retain employees
1.4	Management and support of diversity	Manage diverse and multicultural workforce, treat all people with respect and provide supportive work environment
1.5	Interdisciplinary alignment	Integrate interdisciplinary teams' cooperation to facilitate work processes in a timely manner
2	***Technical competencies***	The technical/functional knowledge, skills, and experience (i.e., the ability to compare, innovate, compile, compute, analyze, coordinate, and synthesize) pertinent to a specific area of construction and/or engineering that allow a worker to execute a job/task at a high level of accomplishment.
2.1	Quality of work	Maintain high standard in executing design, construction, and other related works
2.2	Technical/job knowledge	Sound knowledge of design, construction, engineering, and supervision techniques, skills and procedures
2.3	Commitment to safety	Demonstrate safety awareness and ensure compliance with organizational safety policies and procedures as well as national/international safety regulations
2.4	Planning and organizing of tasks/activities	Plan and organize operational tasks, prioritize multiple competing tasks for effective resource utilization and optimization
2.5	Technical innovation	Develop and adopt innovative planning, design, construction, and engineering processes and technology to enhance competitive advantage
2.6	Business acumen/business management skills	Demonstrate application of business policies and procedures; and understand how business in the construction industry operates
2.7	Market management	Conduct market research, develop strategic alliances with partners/stakeholders to win jobs and enhance market share

No.	Functional competency	Competency definition
2.8	Finance management	Develop yearly spending plan, acquire, and utilize funds, and manage operational/project finances using proven financial management principles
3	***Cross-functional competencies***	The functional knowledge pertinent to processes and practices within the organization that enable the organization to achieve better integration of specialized and wide-ranging cross-functional knowledge. These competencies help to integrate, coordinate, and communicate knowledge among various organizational departments, projects, or work units.
3.1	Cooperation and coordination (collaboration)	Establish and maintain effective both internal (among teams, departments, and projects) and external (partners, stakeholders) cooperation, coordination, and collaboration
3.2	Strategic planning and management	Develop, execute, manage, monitor, and continuously analyze strategic goals to ensure plans, decisions, and actions reflect organizational strategic direction
3.3	Customer/stakeholder focus	Maintain customer value, customer support, customer responsiveness, and prioritizing customer/stakeholder needs to ensure customer satisfaction
3.4	Communications management	Manage internal and external communications through timely generation, collection, storage, and dissemination of information using proper channels
3.5	Interface management	Use network-based interface management system for information sharing and tracking efficiency of operations/projects; and resolving interface issues timely i.e., design errors, system failures, coordination difficulties, and construction conflicts
4	***Production/operations competencies***	The integration of a broad range of knowledge and expertise (i.e., the amalgamation of the specialized knowledge of individuals and other organizational resources) that enables the organization to create value by transforming input to output.
4.1	Construction technology and integration management	Acquire and maintain newly developed technologies and integrate them within operational tasks i.e., planning, design, construction, production, and manufacturing
4.2	Operations and maintenance	Manage organizational operations effectively and maintain the setup, operation, control, maintenance, and improvement of technology that support operations
4.3	Process engineering management	Establish, update, and effectively manage operational/business processes in general and design, construction, and engineering processes in particular
4.4	Construction, production and manufacturing	Effectively plan, execute, monitor and control construction, production and manufacturing tasks of organizational operations/projects
4.5	Product engineering	Ensure product/service is fit for purpose through application of proper quality control during design, production, manufacturing and/or construction processes
4.6	Materials management	Identify, quantify, order, and schedule material needs; ensure availability, and control flow, storage, and conversion of materials to finished product

No.	Functional competency	Competency definition
5	***Construction and engineering research and development competencies***	Competencies that help ensure current processes and products remain competitive. These competencies enable the organization to understand stakeholder needs, and they inspire the organization to strive to create innovative processes and products that give the company a unique competitive edge.
5.1	Business, legal and public policy	Demonstrate knowledge of local/national business policies, codes and regulations related to business management to ensure relevant legal duties and rights in conducting businesses
5.2	Construction laws and regulations	Awareness and understanding of local, national and/or international construction laws and regulations to align organizational operations accordingly
5.3	Management information systems/technology	Acquire, set up, and integrate up to date management information systems/technologies for effective execution/operation of tasks/projects
5.4	New technology/product development	Support research to develop new/emerging technologies to enhance new product/service development and operational/process optimization
6	***Project management competencies***	The organization's project management processes and the continual improvement thereof. By applying the appropriate tools, methods, and concepts to maintain best practices, it is possible to achieve the organization's strategic goals and specific project objectives (i.e., quality, cost, time, safety, etc.).
6.1	Project quality management	Establish and demonstrate quality standards for business processes, operations and projects through proper quality planning, control, and assurance of quality
6.2	Health and safety management	Ensure a safe, secure, and healthy work environment through proper health and safety planning and mitigation strategies
6.3	Project schedule (time) management	Ensure timely completion of projects through proper control, management and update of schedules pertaining to changes
6.4	Project scope management	Ensure project includes all and only all the works required as well as control and manage scope changes for successful project completion
6.5	Project change management	Identify, incorporate and manage effectively all changes made to project baselines scope, time, cost, and quality objectives
6.6	Managing performance	Enable to set direction, building effective teams, and create high-performance climate to support all organizational activities/operations
6.7	Project cost management	Effectively planning, estimating, budgeting, financing, and controlling of costs for successful project completion within approved budget
6.8	Commissioning and start-up management	Create alignment among stakeholders to create a shared vision for project commissioning and start-up based on established acceptance criteria
6.9	Project risk management	Conduct proper planning, identification, analysis of project risks as well as develop risk mitigation and response strategy

No.	Functional competency	Competency definition
6.10	Design development	Manage design development processes in line with statutory/code requirements and client functional/performance requirements
6.11	Project integration management	Coordinating diverse component of projects through state-of-the-art project planning, execution, and change control to ensure successful project completion
6.12	Contract administration	Ensure contracts are in line with applicable national/regional laws and manage contracts in accordance with agreed terms
6.13	Project procurement management	Develop procurement strategy, select suppliers/subcontractors, provide adequate lead time to acquire resources required for projects timely
6.14	Commitment to sustainability	Analyze societal and environmental impact of projects on diverse stakeholders to minimize waste, improve efficiency, and reduce resource use
7	***Supervisory/managerial competencies***	The capabilities of employees who supervise others (especially managers) to engage people, organizations, and partners in order to achieve organizational performance goals that are in line with the organization's values and ethics.
7.1	Engagement	Leading across organizational boundaries to engage broad-based stakeholders and partners in a shared agenda and strategy in developing goals, executing plans, and delivering results
7.2	Management effectiveness/excellence	Effectively manage people, work, and systems with business strategy to harmonize them in meeting short-term and long-term organizational objectives
7.3	Delegation	Nurturing good supervision and management practices through empowering and delegating employees to manage diverse projects, operations, and people within the organization
7.4	Resource management	Effectively plan, acquire, control and manage resources effectively to ensure activities/operations have the resources needed for timely completion

Appendix C.2. List and Definitions of Organizational Behavioral Competencies

No.	Behavioral competency	Competency definition
1	***Organizational attributes***	The organization's processes and practices and its methods of interacting with people (i.e., interactions between people and organizations, people within organizations, and organizations themselves).
1.1	Ability to build trust	Encourage openness and honesty to develop mutual trust among employees and teams across the organization through actions and outcomes
1.2	Competitiveness	Understand competitors in the market to provide better/unique services through incorporating innovative new technologies and value-adding processes and practices
1.3	Adaptability/flexibility	Ability to adapt and adjust effectively to foreseeable changes or unforeseen challenges within the micro/macro environment of the organization
1.4	Achievement drive	Ensure goal clarity among employees and teams at every level to achieve organizational/project objectives and satisfaction of stakeholder needs
1.5	Innovation	Encourage creative ideas that challenge conventional practices to develop novel solutions through integration of new technology for improvement of organizational work processes
1.6	Organizational awareness and culture	Ensure employee commitment to collective objectives that demonstrate unique culture and values associated with the organization
2	***Top management competencies***	Competency of the relatively small group of executives who manage the organization's overall goals, strategy, and operating policies. Top management make decisions about the overall direction and performance of the organization (e.g., CEOs and deputy CEOs).
2.1	Leadership	Establish clear organizational vision and direction as well as lead and align employees/teams towards a shared purpose to achieve organizational goals
2.2	Strategic thinking	Develop strategic vision that reflect strategic direction of the organization and ensure employee/teams work towards this strategic vision
2.3	Judgement	Demonstrate sound judgement in evaluating multiple alternatives effectively weighing best and worst-case scenarios and make decisions based on facts rather than emotions
2.4	Analytical ability/thinking	Demonstrate logical thought process and ability to understand the principles underlying the relationships between facts and apply this understanding in solving problems
2.5	Values and ethics	Respect industry practices that enable to enhance shared beliefs, values, norms across the organization and its operations/projects
3	***Middle management competencies***	Competencies of the largest group of managers within an organization, they are primarily responsible for implementing the policies and plans of top managers. Middle managers translate the overall direction of the organization into specific objectives and plans. They supervise and coordinate the activities of lower-level managers (e.g., department directors, branch managers, project managers).

No.	Behavioral competency	Competency definition
3.1	Interpersonal skills	Ability to with employees/teams from diverse backgrounds by managing their needs and feelings through maintaining open line of communication
3.2	Decision-making	Evaluate available alternatives efficiently and make decisions timely taking the organization's context and strategic direction in to consideration)
3.3	Consultation	Strives to solicit employees'/teams' input when planning and executing tasks as well as making decisions and properly communicate outcomes of the consultation to employees/teams
3.4	Negotiation	Ability to achieve a win-win solution to settle differences with minimum disturbance while maintaining positive relationship
3.5	Reasoning	Ability to think in a logical way in order to arrive at sound decisions or draw conclusions in solving design, contractual, construction, and related engineering problems
3.6	Conflict and crisis resolution/ Issue management	Ability to identify and properly address conflicts to ensure that concerns and issues that threaten organizational/project objectives are resolved effectively
3.7	Assertiveness	Ability to explain complex issues and present cases in a self-assured manner clearly to the employees/teams
4	***First-line management competencies***	Competencies of Managers who supervise and coordinate the activities of operating employees. They implement directions and plans through production/operations and the delivery of services (e.g., team leaders).
4.1	Problem solving	Ability to recognize and evaluate the sign of a problem in a timely manner to analyze relevant information for problem-solving and generate effective solutions by weighing merits of each alternative
4.2	Integrity/high standards	Display strong moral principles and work ethic
4.3	Results orientation	Sets achievable, yet aggressive, goals and constantly enables team members to be top performers who deliver the required results
4.4	Responsiveness	Ensures issues and requests are addressed in a timely manner as appropriate through follow up on issues regularly to meet customer satisfaction
4.5	Influence	Ability to have a continuous influence on employee attitudes and behavior towards a desired result to achieve organizational goals)
4.6	Communications	Ability to convey opinions clearly and concisely to direct employees/teams applying effective and professional communication tools
4.7	Incisiveness	Demonstrate intelligent and clear thinking and capable of getting to the heart of an idea and expressing it clearly and briefly in understandable terms
5	***Individual/personal competencies***	The ability to adopt appropriate, observable behaviors (i.e., attitude and skills) in work-related situations on projects and during other organizational functions/operations.

No.	Behavioral competency	Competency definition
5.1	Reliability/Dependability	Demonstrate responsibility, reliability, and dependability in fulfilling obligations and completing works/tasks in a timely and consistent manner
5.2	Teamwork	Demonstrate the ability to work well harmoniously with staff, co-workers, peers, and managers to achieve common/team goals
5.3	Ethics	Ensures conformity to any organizational, legal, or regulatory framework and industry practices to meet professional standards
5.4	Initiative	Plans work and carries out tasks without detailed instructions and willfully undertake additional responsibilities
5.5	Commitment	Demonstrates dedication to effective job performance by taking action until a task is accomplished in spite of difficult conditions, tight deadlines, or obstacles and setbacks
5.6	Effectiveness	Demonstrates a high level of quality in performing assigned tasks in a way that ultimately leads to higher overall performance
5.7	Self-regulation/control	Display appropriate behavior that enable to control emotion and analyze stressful situations or loss of self-control through open and honest communication
5.8	Motivation	Demonstrates desired behaviors in making an effort at all times to achieve favorable outcomes)
5.9	Resourcefulness	Capable of handling any issues in executing tasks by taking initiative to be part of a solution and competent enough to achieve the desired goals
5.10	Perseverance	Demonstrate self-control when facing challenges during the execution of tasks and stays with a plan of action or position until the desired objective is attained
5.11	Attention to detail	Checks work plans and executions diligently to ensure that all essential details have been considered that enable to identify errors to take corrective actions timely
5.12	Professionalism	Conducts duties with personal and professional integrity strictly abide by applicable (e.g., employer, professional society, client) codes of ethics

Appendix C.3. List and Definitions of Organizational Performance Metrics, and their formulae

Appendix C.3.1. Organizational/operational-level KPIs

KPI No.	KPI name	KPI formula	KPI definition
1.1 Profitability ratio			
1.1.1	Market share	$\frac{\text{Company's volume of work in a market}}{\text{Total volume of work in that market}}$	Company's volume of work as a percentage of an industry's total volume of work over a fiscal year
1.1.2	Market returns	$\frac{\text{Company's revenue in a market}}{\text{Total revenue available in the market}}$	Company's sales/revenue sales as a percentage of an industry's total revenue over a fiscal year
1.2 Financial stability			
1.2.1	Cash flow	$\frac{\text{Cash flow generated from operation}}{\text{Current liabilities}}$	The ratio of cash flow generated from the organization's operation to its current liabilities
1.2.2	Revenue diversification	Predetermined scale (1 - 5) (very poor, poor, average, high, very high)	The business diversification of a company to compete in different market sectors to enhance revenue and business performance

Appendix C.3.2. Organizational/operational-level KPOs

KPO No.	KPO name	KPO formula	KPO definition
2.1 Profitability ratio			
2.1.1	Profitability	$\frac{\text{Company's volume of work in a market}}{\text{Total volume of work in that market}}$	The profit of the company before tax and interest as a percentage of the company's total revenue
2.1.2	Net Income	$\text{Total revenue} - \text{All expenses}$	How profitable a company is over a period of time by subtracting the costs of doing business (e.g., depreciation, interest, taxes, and other expenses) from revenues
2.1.3	Return on Sales	$\frac{\text{Operating profit (net income before tax and inter}}{\text{Net sales}}$	Company's operational efficiency at generating profits from its revenue
2.1.4	Hanging Invoice	$\frac{\text{Accounts receivable}}{\text{Value of sales}} * 100$	The ratio of invoices not yet received from the total value of sales
2.2 Growth			
2.2.1	Revenues growth	$\frac{\text{Revenue this reporting period} - \text{Revenue last reporting}}{\text{Revenue last reporting period}}$	Company's growth (revenue increase/decrease) over time (i.e., compared to the previous reporting period's performance, such as quarterly, and annually
2.2.2	Sales growth	$\frac{\text{Value of sales} - \text{Value of sales in previous period}}{\text{Value of sales in previous period}}$	The ability of a company to increase revenue over a fixed period of time, usually annually
2.2.3	Volume of works growth rate	$\frac{\text{Volume of works for this year} - \text{Volume of works for la}}{\text{Volume of works for last year}}$	Increment/decrement of the company's volume of works (e.g., projects) compared to the previous year
2.2.4	Work force growth	$\frac{\text{Number of employees this year} - \text{Number of employee}}{\text{Number of employees last year}}$	Increment/decrement of employees in the company compared to the previous year
2.3 Business efficiency			
2.3.1	Efficiency ratio	$\frac{\text{Total expenses}}{\text{Total revenue}}$	Company's ability to use its assets and manage its liabilities effectively to generate revenue
2.3.2	Net profit margin	$\frac{\text{Net profit after taxes}}{\text{Total revenue}}$	The percentage of profit after deducting all operating expenses, interest, and taxes that an organization generates from its total revenues

Appendix C.3.3. Organizational/operational-level PerMs

PerM No.	PerM name	PerM formula	PerM definition
3.1 Employee satisfaction			
3.1.1	Employees' satisfaction	Predetermined Satisfaction scale (1–5): (extremely unsatisfied, unsatisfied, neither unsatisfied nor satisfied, satisfied, extremely satisfied)	How content or satisfied employees are with their jobs, including workload, flexibility, work environment, career growth, etc.
3.1.2	Remuneration	Predetermined Satisfaction scale (1–5):	How satisfied employees are with the average remuneration (i.e. wages and salaries) and pay structure (e.g. equal pay for the same job)
3.1.3	Employee turnover rate	$\frac{\text{Employees who left}}{\text{Average number of employees}}$	The percentage of employees who leave an organization during a certain period
3.1.4	Compensation and benefits	Predetermined Satisfaction scale (1–5):	How satisfied employees are with the company's compensation and benefit plan (i.e., both financial and non-financial rewards such as bonuses, peer recognition, work freedom, profit sharing, pension plans, and paid leaves)
3.1.5	Merit increase	Predetermined Satisfaction scale (1–5):	How satisfied employees are with the opportunities for merit increase and promotion within the organization
3.1.6	Social services	Predetermined Satisfaction scale (1–5):	How satisfied employees are with the social services the organization offers such as social and recreational events (e.g., holiday party, annual retreat, and/or family get togethers, etc.), employee assistance programs, tuition reimbursement, and company-paid transportation.
3.2 Customer satisfaction			
3.2.1	Customer satisfaction	Predetermined Satisfaction scale (1–5): (extremely unsatisfied, unsatisfied, neither unsatisfied nor satisfied, satisfied, extremely satisfied)	The degree of satisfaction based on whether the products and/or services provided by an organization meet or surpass customer expectations
3.2.2	Customer retention/loyalty	Predetermined Satisfaction scale (1–5)	The percentage of customers the organization keep relative to the number at the start of the period
3.2.3	Percentage of repeat customers	$\frac{\text{Number of repeat customers}}{\text{Total number of customers}}$	The number of customers who come back to acquire/purchase the organization's products or services for the second (third or fourth) time
3.2.4	Number of complaints	Quantitative (real numbers, percentage)	The frequency and degree of customer dissatisfaction with the products and services of an organization
3.3 Competitiveness			
3.3.1	Company image/reputation	Predetermined Satisfaction scale (1–5): (extremely unsatisfied, unsatisfied, neither unsatisfied nor satisfied, satisfied, extremely satisfied)	How visible a company is within the market (i.e., construction industry), and how the company is perceived and understood by people when the company's name is mentioned
3.3.2	Competitive advantage	Predetermined Satisfaction scale (1–5)	The conditions that allow the company to produce and provide products or services of equal value with a lower cost
3.3.3	Market advantage	Predetermined Satisfaction scale (1–5)	The company's competitive edge gained through superior products or services, lower costs/prices, extensive distribution, and effective promotion

Appendix C.3.4. Project-level KPIs

KPI No.	KPI name	KPI formula	KPI definition
4.1 Quality of work			
4.1.1	Rework factor	$\frac{\text{Total direct cost of field rework}}{\text{Actual construction phase cost}}$	The ratio of total cost incurred to rectify all defects as a percentage of actual construction phase cost
4.1.2	Prevention, appraisal and failure (PAF) Model	$\text{Prevention cost} + \text{Appraisal cost} + \text{Failure cost}$	The defect level of deliverables as perceived and measured by the client or customer
4.2 Safety			
4.2.1	Incidents rate	$\frac{\text{Number of recordable incidents} * 200{,}000}{\text{Total site work hours}}$	The number of recordable incidents occurring among a given number of full-time workers over a given period of time (usually one year, i.e., 2000 hours)
4.2.2	Time lost	$\frac{\text{Amount of time lost to incidents} * 200{,}000}{\text{Total site work hours}}$	The ratio of the time lost to incidents in hours measured over the total hours of site work
4.2.3	Safety performance	$\frac{\text{Number of reportable accidents in reporting period}}{\text{Average number employed in that reporting period}}$	The results of the company's action taken before accidents occur
4.2.4	Accident frequency rate	$\frac{\text{Number of recordable incidents}}{\text{Number of person-hours}} * 1{,}000{,}000$	The number of reportable accidents per 1,000,000 worked hours
4.2.5	Near misses	$\frac{\text{Number of near misses} * 200{,}000}{\text{Total site work hours}}$	The ratio of near misses recorded to the total hours of site work
4.2.6	Behavior-based observation (BBO) rate	$\frac{\text{Number of BBO forms filled}}{\text{Total site work hours}}$	The number of BBO forms filled by workers to evaluate coworkers' safety behavior to identify and avoid risky behaviors to reinforce safe work conditions
Additional metrics provided by participating Company			
4.2.7	Total injury rate	$\frac{\text{Number of injuries}}{\text{Total exposure hours}} * 200{,}000$	
4.2.8	PTRIF	$\frac{\text{Recordable incidents} + (\text{P2 and P3 incidents})}{\text{Total exposure hours}} * 200{,}000$	
4.2.9	Severity	$\frac{\text{Number of lost time workdays}}{\text{Total exposure hours}} * 200{,}000$	
4.2.10	Total incidents rate (non-medical)	$\frac{\text{All incidents (not injuries)}}{\text{Total exposure hours}} * 200{,}000$	

Appendix C.3.5. Project-level KPOs

KPO No.	KPO name	KPO formula	KPO definition
5.1 Effectiveness of planning			
5.1.1	Cost predictability	$\frac{\text{Total cost of changes in works}}{\text{Actual total cost of works}}$	How well an organization predicts costs by comparing actual costs or outturn costs to the original budget
5.1.2	Time predictability	$\frac{\text{Actual cost} - \text{Anticipated cost}}{\text{Anticipated cost}}$	How closely the organization's operations/projects/services were delivered compared to the original schedule
5.1.3	Change cost factor	$\frac{\text{Actual total cost} - \text{Baseline cost}}{\text{Baseline cost}}$	The cost of changes in works as a percentage of actual total cost of works
5.1.4	Cost growth/increase	$\frac{\text{Actual time} - \text{Anticipated time}}{\text{Anticipated time}}$	How the actual cost changes (increases/decreases) over time compared to the initial estimate or baseline cost
5.1.5	Time/schedule growth/increase	$\frac{\text{Actual total duration} - \text{Baseline duration}}{\text{Baseline duration}}$	The variation of actual time expressed as a percentage against anticipated baseline duration

Appendix D. Sample Data Collection Forms

Appendix D.1. Background Information

1.1.1 Name of respondent (Optional): ______________________________

1.1.2 Type of organization you are currently working in

☐ Publicly traded ☐ Privately owned ☐ Employee owned

Other (*please specify*): ______________________________

1.1.3 Where in the organization are you currently working?

☐ Corporate (Head) office ☐ Business (Regional) office ☐ Project office/site

Other (*please specify*): ______________________________

1.1.4 Current position/occupation:

☐ Senior Management (e.g., President, VPs, GMs, Directors/managers of departments, etc.)

☐ Finance Manager ☐ Human Resource Manager

☐ Human resource management staff

☐ Project Manager ☐ Operations Manager ☐ Construction Manager

☐ Project management staff (e.g. Project control, Project coordinators, Quality lead, Safety lead, schedulers, etc.)

☐ Superintendent

Other (*please specify*): ______________________________

1.1.5 How long have you been working in your current stated occupation?

____ Year(s) ____ Month(s)

1.1.6 How long have you been working for your current employer organization?

____ Year(s) ____ Month(s)

1.1.7 How long have you been working in the construction industry (overall experience)?

____ Year(s) ____ Month(s)

1.1.8 Please specify your highest educational degree (*please specify **ALL** that apply*):

☐ PhD ☐ Master's degree ☐ Bachelor's degree

☐ College diploma ☐ Technical, vocational, or trade school

Other (*please specify*): ______________________________

1.1.9 What is your age (years)?

☐ 18–30 ☐ 31–40 ☐ 41–50 ☐ 51–60 years ☐ >60

1.1.10 What is your gender?

☐ Male ☐ Female ☐ Prefer not to answer

Appendix D.2. Sample Data Collection Form for Organizational Functional Competencies

2.3 CROSS-FUNCTIONAL COMPETENCIES

Cross-functional competencies: The functional knowledge pertinent to processes and practices within the organization that enable the organization to achieve better integration of specialized and wide-ranging cross-functional knowledge. These competencies help to integrate, coordinate, and communicate knowledge among various organizational departments, projects, or work units.

Maturity						**Impact on Organization's Performance**						
NA	*Level 1*	*Level 2*	*Level 3*	*Level 4*	*Level 5*	*Level 1*	*Level 2*	*Level 3*	*Level 4*	*Level 5*	*Level 6*	*Level 7*
Not applicable	*Informal*	*Documented*	*Integrated*	*Strategic*	*Optimized*	*Extremely low*	*Very low*	*Low*	*Medium*	*High*	*Very high*	*Extremely high*

No.	**Competency**	**Description of Competency**	**Maturity**						**Impact on Organization's Performance**						
2.3.1	Cooperation and coordination (collaboration)	Establish and maintain effective both internal (among teams, departments and projects) and external (partners, stakeholders) cooperation, coordination and collaboration	NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.2	Strategic planning and management	Develop, execute, manage, monitor and continuously analyze strategic goals to ensure plans, decisions, and actions reflect organizational strategic direction	NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.3	Customer/stakeholder focus	Maintain customer value, customer support, customer responsiveness, and prioritizing customer/stakeholder needs to ensure customer satisfaction	NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.4	Communications management	Manage internal and external communications through timely generation, collection, storage, and dissemination of information using proper channels	NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.5	Interface management	Use network-based interface management system for information sharing and tracking efficiency of operations/projects; and resolving interface issues timely i.e., design errors, system failures, coordination difficulties, and construction conflicts	NA	1	2	3	4	5	1	2	3	4	5	6	7
	Other (*please list criteria and evaluate*)														
2.3.6			NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.7			NA	1	2	3	4	5	1	2	3	4	5	6	7
2.3.8			NA	1	2	3	4	5	1	2	3	4	5	6	7

Appendix D.3. Sample Data Collection Form for Organizational Behavioral Competencies

3.3 MIDDLE MANAGEMENT COMPETENCIES

Middle managers: The largest group of managers within an organization, they are primarily responsible for implementing the policies and plans of top managers. They translate the overall direction of the organization into specific objectives and plans. They supervise and coordinate the activities of lower-level managers (e.g., department directors, branch managers, project managers). Please evaluate the following competencies considering middle level managers.

Agreement							**Impact on Organization's Performance**						
Level 1	*Level 2*	*Level 3*	*Level 4*	*Level 5*	*Level 6*	*Level 7*	*Level 1*	*Level 2*	*Level 3*	*Level 4*	*Level 5*	*Level 6*	*Level 7*
Strongly disagree	*Disagree*	*Slightly disagree*	*Neither disagree nor agree*	*Slightly agree*	*Agree*	*Strongly agree*	*Extremely low*	*Very low*	*Low*	*Medium*	*High*	*Very high*	*Extremely high*

No.	**Competency**	**Description of Competency**	**Agreement**							**Impact on Organization's Performance**						
3.3.1	Interpersonal skills	Ability to with employees/teams from diverse backgrounds by managing their needs and feelings through maintaining open line of communication	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.2	Decision-making	Evaluate available alternatives efficiently and make decisions timely taking the organization's context and strategic direction in to consideration)	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.3	Consultation	Strives to solicit employees'/teams' input when planning and executing tasks as well as making decisions and properly communicate outcomes of the consultation to employees/teams	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.4	Negotiation	Ability to achieve a win-win solution to settle differences with minimum disturbance while maintaining positive relationship	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.5	Reasoning	Ability to think in a logical way in order to arrive at sound decisions or draw conclusions in solving design, contractual, construction, and related engineering problems	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.6	Conflict and crisis resolution/ Issue management	Ability to identify and properly address conflicts to ensure that concerns and issues that threaten organizational/project objectives are resolved effectively	1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.7	Assertiveness	Ability to explain complex issues and present cases in a self-assured manner in a way that is clear to the employees/teams	1	2	3	4	5	6	7	1	2	3	4	5	6	7
	Other (*please list criteria and evaluate*)															
3.3.8			1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.9			1	2	3	4	5	6	7	1	2	3	4	5	6	7
3.3.10			1	2	3	4	5	6	7	1	2	3	4	5	6	7

Appendix D.4. Sample Data Collection Form for Subjective Organizational Performance Metrics

4.3 OPERATIONAL—PERCEPTION MEASURES (PerMs)

Perception measures (PerMs): Indicators dependent on the manager's/individual's perception and/or focus, often measured through surveys and interviews. PerMs can be either leading or lagging indicators depending on when they are measured.

No.	PerMs	PerM Description	**Satisfaction Scale**					
			Unable to evaluate	***Extremely dissatisfied***	***Dissatisfied***	***Neither dissatisfied nor satisfied***	***Satisfied***	***Extremely satisfied***
4.3.1	**EMPLOYEE SATISFACTION**							
4.3.1.1	Employees' satisfaction	How content or satisfied employees are with their jobs, including workload, flexibility, work environment, career growth, etc.	UE	1	2	3	4	5
4.3.1.2	Remuneration	How satisfied employees are with the average remuneration (i.e. wages and salaries) and pay structure (e.g. equal pay for the same job)	UE	1	2	3	4	5
4.3.1.3	Compensation and benefits	How satisfied employees are with the company's compensation and benefit plan (i.e., both financial and non-financial rewards such as bonuses, peer recognition, work freedom, profit sharing, pension plans, and paid leaves)	UE	1	2	3	4	5
4.3.1.4	Merit increase	How satisfied employees are with the opportunities for merit increase and promotion within the organization	UE	1	2	3	4	5
4.3.1.5	Social services	How satisfied employees are with the social services the organization offers such as social and recreational events (e.g., holiday party, annual retreat, and/or family get togethers, etc.), employee assistance programs, tuition reimbursement, and company-paid transportation.	UE	1	2	3	4	5
	Other (*please list criteria and evaluate*)							
4.3.1.6			UE	1	2	3	4	5
4.3.1.7			UE	1	2	3	4	5
4.3.1.8			UE	1	2	3	4	5
4.3.2	**CUSTOMER SATISFACTION**							
4.3.2.1	Customer satisfaction	The degree of satisfaction based on whether the products and/or services provided by an organization meet or surpass customer expectations	UE	1	2	3	4	5
4.3.2.2	Customer retention/loyalty	The percentage of customers the organization keep relative to the number at the start of the period	UE	1	2	3	4	5
4.3.2.3	Percentage of repeat customers	The number of customers who come back to acquire/purchase the organization's products or services for the second (third or fourth) time	UE	1	2	3	4	5