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Quality Deviation Requirements in Residential Buildings: Predictive Modeling of The Interaction between Deviation and Cause

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DECLARATION

I declare that the following dissertation titled "*Quality Deviation Requirements in Residential Buildings: Predictive Modeling of the Interaction between Deviation and Cause*" is the result of my own research towards a doctoral degree. It does not contain any materials previously published or written by another person except as cited in the references. Nor has it been accepted for any degree or concurrently submitted in candidature of another degree. The thesis is less than 100,000 words in length exclusive of tables, maps, and references.

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ABSTRACT

Quality deviation and construction defects are perennial issues in the creation of the built environment. Residential buildings in particular tend to be vulnerable to poor design and construction leading to project failure, with state-of-the-art techniques of quality control (QC) rarely implemented; there is an absence of sophisticated task analysis in construction able to break down packages of work into manageable tasks and sub-tasks. Notwithstanding the publication of sub-task requirements (STRs) in building codes, there is a lack of literature concerning task and sub-task sensitivity and susceptibility to deviation. In-depth task analysis to date appears to have been overwhelmed by volumes of construction research effort that have largely focused on after-the-fact defect and quality issues. This study sought to bridge the knowledge gap by predictive modeling of the interaction between deviation and cause, through applying a task-based analysis of deviation. This study assessed the nature of requirements of sub-tasks and the interaction between these requirements and direct causes of deviation in the residential construction sector; development of an approach to determine patterns of quality deviation and defect occurrence in construction was undertaken using a novel quality deviation classification system to model and simulate interactions between deviations of STRs and the direct causes of deviation from quality norms.

This study: *identified the factors relevant to quality deviation* (87 factors were tested for content validity by a panel of experts and a final number of 65 were examined); *measured susceptibility to deviation (*the susceptibility of sub-task requirements to quality-norm deviation was found to vary with complexity and code compliance when statistical process control measured quality practices for 17 STRs respectively across 27 separate construction sites); *classified STRs* (the frequency of occurrence for six classes was determined); *ranked sensitivity to defect from one STR across all STRs* (association between degree of deviation and STR established sensitivity to 'defective-work'); and, *applied a Bayesian belief network-BBN (*quantification identified unique causation patterns of quality deviation for each STR).

This study found that: the variation in sensitivity to quality deviation STR-to-STR should be considered during the design and execution phases of construction; inspection effort cannot be exerted equally across STRs and should be designed and distributed based on the sensitivity of the relevant STRs to deviation; *no* specific benefit is to be gained from conducting uniform inspection procedures, that is, applying the same inspection effort, across all STRs is of no benefit. The study found that the patterns of direct causes of deviation from quality norms are unique for each STR, and that causation patterns cannot be generalised.

The work conducted provides quality managers with a new visualization tool to clarify the STR-specific cause of quality deviation pathways when creating the built environment.

RELEVANT PUBLICATIONS

Chapter 6 Almusharraf, A. & Whyte, A. (2015). "Task-based defect management: anatomical classification". *Built Environment Project and Asset Management*, confirmed-acceptance (in-press-BEPAM-02-2015-0006. R1).	Accepted in 09/2015
Chapter 5 Almusharraf, A. & Whyte, A. (2015). "Project Sub-Task Requirements (STRs): Measuring Susceptibility to Quality-Deviation and Defect". (Paper has been submitted to the Journal of Construction Engineering and Management (ASCE) after revised the reviewers' comments).	Under process of publication
Almusharraf, A. & Whyte, A. (2013). "Defects Prediction Towards Efficincy Gains in Construction Projects." In *The 1st Australasia and South East Asia Conference in Structural Engineering and Construction* (ASEA-SEC-1), Nov 28, 2012, Perth, Western Australia: Research Publishing Services.	Accepted in 07/2012
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Almusharraf, A. & Whyte, A. (2015). "Sensitivity of Sub-tasks Requirements STRs towards Quality Deviations and Construction Defects." Paper presented at *the eighth international structural engineering and construction conference* (ISEC-8), Sydney, Australia, November 23-28, 2015. Confirmed-acceptance (In-press).	Accepted in 05/2015

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List Of Acronyms

χ^2	Chi-Square test
ρ	Spearman's rho
$\Delta\mu$	Difference mean values for test–retest measurements
Σ	Summation
δ_x	Impact of a unit-change
ϕ	Bar diameter
$\lvert z \rvert$	Absolute value of z-scores
η^2	Eta squared - effect size
σ	Standard deviation
A_{st}	Steel cross-section area
A_g	Gross area of the concrete section
ACI	American Concrete Institute
ANN	Artificial neural network
ANOVA	One-way analyses of variance
BBN	Bayesian Belief Network
BN	Bayesian Network
BRE	Building Research Establishment
C_p	Capability of a process
C_{pl}	Capability of a process for the lower specification limits
C_{pu}	Capability of a process for the upper specification limits
C_{pk}	Capability of a process average to the centre of the specification limits
CI	Continuous improvement
CPI	Capability process index
CPD	Conditional Probability Distributions
CPT	Conditional Probability Tables
De_x	Direct effect
D	Width
d	Depth
d_b	Bar dimension
df	Degree of freedom
F	Fisher statistic
GA	Genetic Algorithm
GDP	Gross domestic product
HRBS	Hierarchical Risk Breakdown Structure

ISO	International Organization for Standardization
LSL	Lower-specification-limit
MI	Mutual information
MMRE	Mean Magnitude of Relative Error
MRE	Magnitude of Relative Error
OR	Odds ratio
P	The probability of the samples being within the specification limits
P_l	The probability of the samples for the lower specification limits
P_u	The probability of the samples for the upper specification limits
PAF	Prevention, appraisal and failure
PPM	Parts-per-million
QA	Quality assurance
QC	Quality control
SBC	Saudi Building Code
SD	Standard deviation
SD	System dynamics
SE	Standard error
SEM	Structural equation modelling
SNA	Social network analysis
SPC	Statistical Control Process
STR	Sub-Task Requirements
TQM	Total quality management
USL	Upper-specification-limit
WBC	Work breakdown structure

CHAPTER 1: Introduction

1.1 Background of the Study

Construction, the preparing for and formation of buildings and other structures, is an essential sector of every economy (Hillebrandt, 2000; Su, Lin & Wang, 2003). The construction sector has a significant impact on quality of life, due to its positive effect on other areas vital to the overall economy (Su et al., 2003; Forbes & Ahmed, 2011). There are a number of unique aspects of the construction sector, which differentiate it from other commercial sectors and reflect its importance. Firstly, it is a sector vital for growth. It is a sector closely associated with socio-economic development through its provision of residential, commercial, and industrial spaces (Ofori, 2012).

Another aspect of the construction sector of interest is its size. Construction as an industry is one of the largest product-based activities in the world (Loushine et al., 2006). One can also appreciate the size of the construction sector through reflecting on its direct contribution to gross domestic product (GDP) (Forbes & Ahmed, 2011; Lopes, 2012). Investors typically target the construction sector (The Construction Industry Development Board [CIDB], 2004), and as a labour-intensive industry, it is an important source of employment and wealth distribution mechanism for society (Lopes, 2012).

However, problems exist. Quality deviation and construction defects are a perennial issue for the sector. Residential buildings in particular tend to be vulnerable to poor design and construction efforts leading to project failure. Quality management interventions are applied in construction projects, however, state-of-the-art methods and techniques appear to be rarely implemented according to researchers (Jaafari, 1996; Irani & Holt, 2000; Pheng & Teo, 2003; Haupt et al., 2004; Turk, 2006). Post-production quality assurance appears to be an example of poorly developed or superficial quality management according to Jaafari (1996). Quality interventions are reported to be hindered by financial, practical, and perception constraints (Jaafari, 1996; Chileshe, 1996; Bubshait & Al-Atiq, 1999; Love, Mandal & Li, 1999; Love, Li, Irani & Holt, 2000; Pheng & Teo, 2003; Haupt et al., 2004; Turk, 2006).

Quality control ('QC') typically involves process and product inspection with the goal to identify deviation from requirements (Kakitahi et al., 2011). QC is an important quality intervention however its implementation in the construction sector is also hindered by financial, practical, and perception constraints. The Building Research Establishment in the United Kingdom found that persons responsible for QC lacked motivation to conduct QC appropriately and in good faith. The Establishment found that insufficient time allocation tended to underpin a lack of bona fides and ultimately led to the continuation of sub-optimal and dangerous practices on site (Love & Edwards, 2004b).

Quality deviation and manifest defects in construction projects cause time and cost overruns. Wastage, rework, legal liability including claims on warranties, and adverse implications for client satisfaction and company good will are related consequences of poor design and construction (Fox, Marsh & Cockerham, 2003). From the point of view of the principal contractor, quality deviation and manifest defects increase the cost of completion and decrease the value of the project. Manifest defects have been found to increase the cost of completing projects by between 2 and 20% (Burati et al., 1992; Jafari & Love, 2013; Josephson & Hammarlund, 1999; Love & Li, 2000).

The relative increase in project completion costs is more acute in the residential sector (Love & Li, 2000). Conflict arises rapidly in the residential sector when defects result in budget and schedule deviation constituting breaches of contract and causing expectation and reputation related issues (Love & Edwards, 2004a; Palaneeswaran, 2006; Almusharraf & Whyte, 2012; Whyte, 2014). The occurrence of manifest defects and rework typically suggests to clients that the contractor may be unreliable and/or unprofessional and often causes further inquiry into the overall quality of the work (Eden et al., 2000; Palaneeswaran, 2006).

One intervention which saves time and costs in the residential and the industrial construction sectors is the early discovery of a need for rework. In most cases, the earlier quality deviations and manifest defects are identified, the lower the relative cost of addressing the defects will be (Cooper, 1993; Eden et al., 2000). Rework in the planning stages of project delivery is easier to accommodate than rework required during the construction phases (Love & Edwards, 2004a). Similarly, defects identified after the construction phases and during client handover, are likely to involve more complicated rework and expose the contractor to more substantial financial consequences (Forcada, Macarulla & Love, 2012). Rework risk can typically be mitigated through contract, project, quality and value management interventions (Palaneeswaran, 2006).

One approach to minimise quality deviation and defect occurrence in the construction sector is meaningful consideration of the nature of tasks relevant to the project (Tah & Carr, 2000; Love et al., 2009; Priemus and Ale, 2010; Lopez et al., 2010). A task is "a piece of work that has been given to someone" or "a job for someone to do" (Merriam Webster, 2012). Successful project delivery requires that the contractor is able to plan, coordinate, and execute, essential tasks. The concept of a "task" has taken on substantial theoretical significance in light of the increasing importance of goal setting with respect to construction project delivery (Campbell, 1988).

Notwithstanding this, task analysis is often absent in such projects. Organisations often fail to appropriately break down packages of work into smaller manageable tasks and sub-tasks. Such decomposition is not a difficult process, however, it is time-consuming (Love et al., 2009). In other projects, there can be disagreement as to the nature of each task (Liu & Li, 2012; Wood, 1986). Priemus and Ale (2010) argue that misunderstanding of the nature of tasks is a source of construction defect, which can occur at any stage of the project's lifespan. Moreover, there is lack of literature concerning the sensitivity and susceptibility of tasks. To date, construction research typically focuses on after-the-fact defect and quality issues at the expense of any in-depth task analysis (Tah & Carr, 2000; Mills, Love & Williams, 2009; Forcada et al., 2012).

This study investigates defects from the view of the nature of requirements of sub-tasks and the interaction between these requirements and direct causes (e.g., worker-related underperformance) of quality deviation in the residential construction sector.

1.2 Statement of the Problem and Gap of Knowledge

Quality deviation resulting from non-compliance with project specifications and building codes and resultant onsite defects in as-built components, lead to rework, budget and schedule overruns, and cause life-cycle maintenance concerns (Ahzahar et al., 2011; Love et al., 2013). Rework of failing building elements arises largely from deviations from quality procedures (Lopez et al., 2010; Vlassis et al., 2007). For instance, the violation of steel cross-sectional areas (A_{st}) of longitudinal reinforcement for compression members by exceeding minimum requirements causes a deficiency in functionality and proneness to building collapse (American Concrete Institute, 2008: ACI 318, Section 10.9.1).

Defects, departures from established requirements, so severe that rectification is mandatory, have become “an [unfortunate but] accepted part of the building process” (Burati & Farrington, 1987; Georgiou, 2010; Mills et al., 2009). Deviations of such severity as to require corrective action add substantial costs to construction. More alarmingly, even minor defects can have catastrophic consequences including sudden collapse and fatalities (Daniel et al., 2014). Waste from quality deviation, as a percentage of a building projects’ value, is argued to range from 5 to 20% (Jafari & Love, 2013). Burati et al. (1992) found that quality deviations resulted in a 12.4% loss in project value. Similarly, Josephson and Hammarlund (1999) showed that 2%-6% of contract values are wasted in residential building work from rectification of on-site non-conformances. Indeed beyond budget shortfalls, quality deviation reduces work satisfaction levels of project participants, creates conflict and dispute between stakeholders, and reduces confidence in the built asset.

Defect classification has been seen a necessary step towards improving quality in the construction section (Davies et al., 1989; Mills et al., 2009). Researchers have advocated numerous approaches with some focusing on the construction element itself where the defect occurs, such as within the floors, ceilings, or roofs (Georgiou, 2010; Forcada et al., 2013). Others have used the location of the defects as a descriptor, such as in the kitchen, bedroom, or garage (Forcada et al. 2013). Another approach has been to classify the defect based on its type, such as leaking roofs, cracking, or footings (Georgiou, 2010; Mills et al., 2009), or the type of building in which it occurs, such as residential, commercial, or industrial (Mills et al., 2009). Defect classification to date has provided some illumination on the nature of their occurrence. However, the pre-existing classification literature arguably suffers from limited generalisability due to fact any relationship between defects and formal industry benchmarks such as building code regulations, have been neglected.

Davis et al. (1989) advocated an approach to quality which focused on measurement and “conformance to requirements”. The authors argued that deviation could be best managed through measurement. As part of the authors' proposed “anatomy of deviation,” they argued that managers needed to identify the “specific tasks [which] were involved in the deviation.” The team concluded that an objective basis was required for measuring quality. The authors stopped short of empirically examining the specific nature of tasks and the tasks' sensitivity to deviation. The majority of defect investigations since Davis et al. have failed to incorporate an objective benchmark from which deviation could be better understood. Tang et al. (2004) studied deviations related to tasks involved with placing typical floors. The study however was limited to a focus on costs of non-conformance as opposed to investigating frequency and severity of prescribed requirement non-conformance.

This study aims to bridge the gap of identifying the “specific tasks [which] were involved in the deviation” as described by Davis et al. (1989) through proposing and testing the sensitivity and the application of an anatomical classification approach to defect management. The study applies a hierarchical-decomposition approach (Figure 1.1) decomposing packages of work (e.g., 1st floor structure), into components (e.g., columns), into tasks (e.g., rebar), into sub-tasks (e.g., longitudinal bars), and then considering sub-task requirements ('STR') as prescribed by building codes (e.g., steel cross-section A_{st} : $001A_g \geq A_{st} \leq 0.08A_g$).

The study (shall in the chapters that follow describe in detail how it) uses data gathered from 17 sub-tasks and their respective building code requirements. The study, after completing the analysis of quality deviation of STRs, applies a Bayesian Belief Network (BBN) to create an interaction network between quality output (perfect-work, acceptable-work and defective-work) and direct causes (as shown in Figure 1.1 and re-described also in Fig 7.11 and Chapter 7) ultimately identified from the literature (with 65 factors reviewed subsequently).

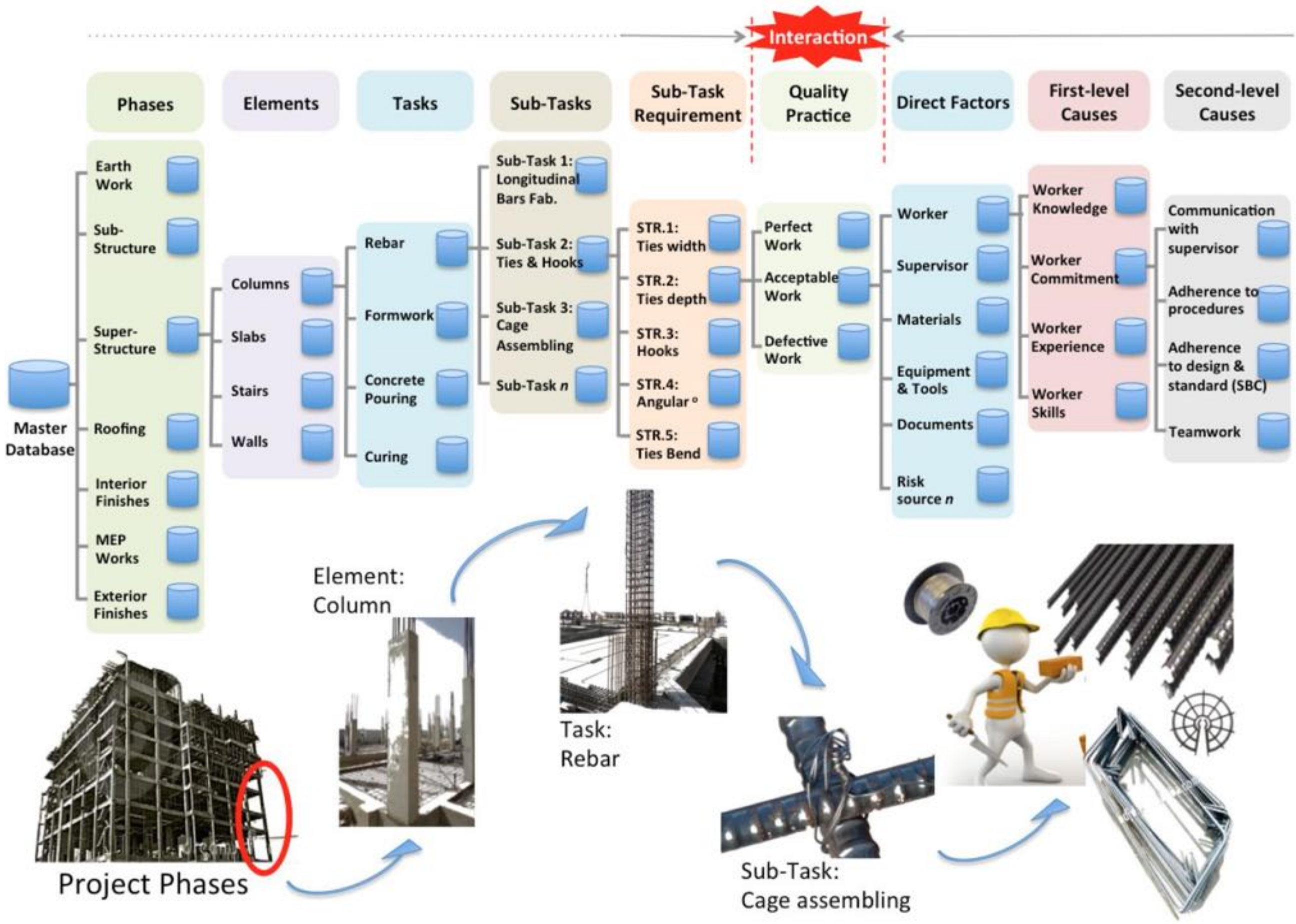


Figure 1.1 Hierarchical decomposition approaches for project tasks

1.3 Research Aim and Objectives

1.3.1 Study's Aim

The main objective of this study is to develop an approach to determine patterns of the quality deviations and defect occurrence in the construction industry using a novel quality deviation classification system and novel model to simulate interaction between deviations of STR and direct causes, these being task resource and task surroundings conditions.

1.3.2 Objectives

Six objectives have been proposed to achieve the main aim of this study as the following:

1. Identify the factors relevant to quality deviation and defect occurrence in the construction industry from literature review (Chapter 2).
2. Measure the susceptibility of individual STRs to quality deviations to determine if isolated STRs exhibit different deviation patterns (Chapter 5). To address this objective, the researcher identified design specifications for specific sub-tasks from requirements from building codes (e.g. SBC and ACI) and project documentation (e.g. drawings, specifications, bill of quantity, etc.), and used these parameters to set targeted measurements and range of tolerance and maximum/minimum boundaries for each specific sub-task. These points then used to measure deviation degree.
3. Classify each STR into one of six novel classes as a means to better understand patterns of deviation occurrence (Chapter 6). To address this objective, an anatomical analysis for each isolated STR is conducted to present performance for each STR. The frequency of occurrence for each of the six classes is determined and used to assist and better understand patterns of deviation occurrence; identification of deviation source as either design phase or execution phase through classifying the degree of sub-task deviation against design specifications and building code requirements.

4. Measure and rank the sensitivity towards each class from one STR across all STRs; to determine accurately the level of the variation and sensitivity between the STRs (Chapter 6).
5. To develop and test a novel BBN-based model capable of simulating realistic interaction of quality deviation with its causes at the STR level (Chapter 7 and 8).
6. Provide recommendations with respect to the nature of STRs in concrete structural construction and model quality deviation and defects (Chapter 8 and 9).

1.4 Scope of the Research

There is already a large body of literature available on deviation and defects in construction projects due to inappropriate quality practices that focus on the type of defect (e.g., cracks, functionality, entrapped water, floor moisture) (Ilozor et al., 2004). It is argued that studies to date have neglected the role of the nature of tasks. There has been an absence of investigating the susceptibility of different tasks to deviation. Specifically there have been very few studies in the field interested in the relationship between satisfaction of requirements of building codes (e.g., the acceptable ratio of cross-sectional area of rebar steel A_{st}: $0.01 \geq A_{st} \leq 0.08$) and defect occurrence. The scope of this research is the sub-task requirement as a unit of analysis. The approach represents preciseness compared to other studies in the field. The unit of analysis was chosen to attempt to show relationships between quality deviation, defects, the nature of tasks involved in construction and causes that leading to deviations and defects in each STR.

At the level of concrete structure members, the study focuses on the STRs of sub-tasks related to column construction. Column construction was chosen as a focus as columns are important as the compression members of construction concrete structures. Furthermore, as implementing the sub-tasks of columns tends to be rapid, data collection from a range of cases is therefore convenient. Finally, the sub-tasks related to columns are accessible and each construction structure has a number of different columns within the design which enables the comparison of variations. The investigation focused on multiple on-site cases studies, targeting 17 STRs related to column construction.

In relation to geographical area, the scope of the study is limited to residential project locations in Saudi Arabia. Two building code requirements (Saudi Building Code SBC-305A & B and American Concrete Institute Code ACI-318A & ACI-117) often adopted in Saudi Arabia are used. Saudi Arabia has been chosen to apply the multiple cases studies in order to achieve the research objectives.

1.5 Significance of the Study and Research Contributions

Even though a large body of research has sought to investigate different aspects of construction quality control practices (Robinson-Fayek et al., 2004), there have been few, if any, studies that have focused on the nature of relevant tasks in the construction process, their specifications and/or their requirements. Love et al. (2009) argued that although deconstructing the package of work or specific activity into smaller manageable tasks or sub-tasks is not a difficult process, organisations find it time-consuming procedure. The implication is a need for exploring the *nature* of relevant tasks in construction processes. The present study attempts to address the need, by examining the sensitivity of STRs to deviation.

Overcoming issues arising from quality deviation and defects in construction, in particular those arising from STRs, depends on identifying significant causes. By investigating which STRs previously experienced high variations in quality, analysts will develop a better understanding of patterns inherent to each STR. Such an appreciation of a STR's sensitivity to deviation will help to develop more proactive means of quality management. Those STRs most susceptible to deviation can be prioritized for control.

There are very few studies concerned with the measurement of quality deviation against building code requirements at the sub-task level. This study applies a capability process index (CPI), a rigorous Statistical Control Process (SPC) tool and popular in manufacturing, as a benchmark. The SPC tool is used in manufacturing and construction and aims to reflect the extent quality practices are consistent across two industries. The tool also serves to give insight on quality practice in construction projects in Saudi Arabia. The study also will provide considerable generalizations of the quality practices in Saudi Arabia and make recommendations for the future of quality control and construction inspection.

Another contribution is the classification of relevant construction-based tasks into micro-level manageable STRs. By focusing on the STR level, it is possible to develop an understanding of the respective deviation patterns for all STRs. The advantage is being able to use knowledge of STR deviation patterns to determine more appropriate allocation of inspection resources to avoid deviation occurrence at the earliest instance. The study provides a six-class classification system, which provides a platform for researchers to model future investigations into accurate defect analysis.

The study also provides a dynamic model for the prediction of direct causes of deviation related to STRs. The model uses a BBN approach to assess relationships between STRs and quality deviation. The study also provides analytical generalizations with respect to the model proposed based on the BBN and recommendations concerning the proposed model and causes of quality deviation in Saudi Arabia. These recommendations are aimed at improving QC processes and inspection performance through permitting the use of deviation pattern information for each STR.

The study also enables the visualization of causation paths of quality deviation. Analysts using QC software based on the development of a wide database of STRs relevant to building construction could use visualization of causation as an inspection tool. Added value could arise from further research simulating STR deviation patterns and the development of an augmented reality platform. Solutions to aid the prevention of quality deviation and construction defects could be developed based on the history of each STR.

1.6 Research Approach and Design

A multiple-case design is applied. Seventeen (n=17) separate case studies (at 27 construction projects) were analysed. The research instrument's purpose and format were developed. The precise direct measurements that would be conducted were ascertained, and observation checklists and schedules, and document analysis techniques (i.e., drawings, specifications, and bill of quantities) were developed. An interview structure for project supervisors (project or quality manager) and labour was developed. Once instruments and processes were determined, data collection commenced.

A number of inferential statistical procedures were applied. The first, as mentioned, was a CPI analysis. The analysis sought to determine the capability of a process C_p and C_{pk}, a statistical index referring to process performance based on pre-set specific requirements. Susceptibility of each STR to exposure to quality deviation was identified and SPC amounts C_p and C_{pk} were employed to measure quality practices (as described in Chapter 5). The Chi-Square (χ^2) test of contingencies was another inferential statistical procedure conducted. Chi-Square (χ^2) analysis is used to investigate association between two or more categorical variables. In this research, Chi-Square (χ^2) analysis was used to determine association between degree of deviation and the STR (as described in Chapter 6).

Odds ratio analysis was also used in this study (also described in Chapter 6). Odds ratio analysis is a flexible and robust statistical parameter of how strongly are two variables related. It quantifies variable relationship strength or effect size. It is also used to evaluate ratio between odds of an outcome occurring against the odds of it not occurring. In this research, odds ratio analysis was used to rank the sensitivity degree of all STRs.

Finally, a Bayesian-belief-network BBN approach was used to quantify the most significant causes through observing and predicting of interaction between deviation level in terms of quality practices for each STR (five STRs have been examined: STR.1, STR.5, STR.13, STR.15 and STR.16) and which kind of causes that related to the deviation for each STR (as described in Chapter 7 and 8).

1.7 Structure of Thesis

The thesis consists of nine chapters. Chapter 1 introduces the study through providing a background and statement of the research problem. The chapter outlines the primary aim of the research as well as its six objectives. The scope and significance are explained, and an overview to the research approach, design, and structure are provided.

Chapter 2 provides a topic-by-topic review of the construction literature related to quality practices. The review in particular focuses on research and commentary concerning quality deviation and construction defects, and especially in relation to concrete structure requirements. A review of causes of deviation and existing models of quality deviation is provided. The chapter aims to identify issues yet to be adequately explored, and to isolate the most important variables to the research problem.

Chapter 3 presents the method of the study. The chapter starts by providing the conceptual framework of the research and the philosophical assumptions applied to the development of the framework. The chapter also provides the research design and elaborates on the justification for the selection of a multiple-case approach involving 17 cases (at 27 construction projects). The development of the data collection instrument is described including the role of documentation, structured interviews, observation, and direct measurement processes. The processes for attesting the instrument's content validity are also outlined. The rationale for, and application of, data analysis techniques applied in the study are discussed in the chapter. Finally, the chapter outlines the tests of data validity and reliability that were conducted.

Chapter 4 presents descriptive analysis results. The chapter begins by screening of the data. The data is analysed in terms of frequency and numerical qualitise, and is visualised. A discussion of initial findings is included in the chapter. Importantly, the chapter provides the results to an ANOVA test on quality and a reliability test involving each of the 17 STRs for the first 5 projects. The results were satisfactory and supported subsequent statistical analysis.

Chapter 5 incorporates what the researcher proposes is an objective benchmark (design specifications, building code requirements, and actual output) from which deviation in construction can be better understood. The chapter explores the nature and pattern of tasks and their susceptibility to deviation by dividing the tasks into sub-tasks. Seventeen STRs are defined in a quantitative approach to case studies of 27 residential structures. The chapter outlines to the use and results of SPC parameters C_p and C_{pk}. The susceptibility of each STR to deviation is presented in the chapter along with recommendations.

Chapter 6 proposes an anatomical classification approach to defect management based on design specification, building code requirements, and actual output of 17 STRs related to compression concrete members (i.e., columns) at 27 construction projects. The chapter also provides results to tests of the application of such an approach. The chapter proposes six classes of deviation based on the extent that sub-task was prone to be "perfect", "acceptable" or "defective" in relation to acceptable tolerance, and the source of deviation, namely, either the design or execution phase. The chapter also presents the results of *Chi-square* and *Odd Ratio* tests which were employed to measure and analyse the sensitivity of each STR to exposure to quality deviation and construction defects.

Chapter 7 discusses the development of a Bayesian-belief-network BBN model with the capability of linking interaction between the nature of task with the direct factors related to the task resources and surrounding conditions. The chapter presents a description of Bayes theorem and its applications providing a conceptual background on BBN on which the proposed models have been based. The chapter also discusses the different metrics that were used in the development of the model, and examines the way BBN has been used in the construction industry to date. The chapter contributes to the body of construction defect knowledge through discussing quality deviation and defects analysis using the proposed BBN model.

Chapter 8 extends on the work in Chapters 5 and 6. The chapter reports on quantification of causes through observation and prediction of interaction between deviation level in terms of STR quality practice and related causes using a BBN approach. The chapter reports on the significant causes of deviation for five STRs identified using a data set of 135 cases for each STR from 27 construction projects. The chapter provides the patterns of causes amongst STRs and discusses implications of the results with the aim to assist quality managers in the detection and control of deviation. The chapter provides analytical generalizations with respect to the model proposed based on the BBN, and recommendations as well as visualization tool to clarify causes paths of quality deviation.

Finally, Chapter 9 provides a summary of the key research findings, highlighting contributions made to pre-existing body of knowledge, and implications for quality practices in construction industry. The chapter also discusses the limitations of the study, and provides recommendations for future research. Following the reference list, supplementary information is provided in the Appendices.

1.8 Chapter Summary

The chapter provided a background and statement of the research problem, namely, construction defects prediction. The chapter presents the research objectives based on gaps identified in the pre-existing literature. The scope, significance, and research design of the research project are also described. The thesis structure including nine chapters is outlined based on each chapter's purpose and methods.

CHAPTER 2: Literature Review

2.1 Introduction

Chapter 2 reviews the existing literature in relation to quality practices in construction industry, in particular, residential building projects. The importance of the construction industry and quality management interventions applied in the sector were overviewed. The chapter seeks to identify issues of deviation and defect manifestation that have been inadequately investigated by previous studies. Past research efforts into the causation of quality deviation and defects are reviewed and the most salient factors influencing deviation from quality are identified. The chapter is also concerned with the task-level of construction with the characteristics of specific tasks being analysed. Finally, this chapter provides a review of pre-existing modeling approaches to quality deviation and defects causation.

2.2 Construction Industry

Construction is the preparing for and forming of buildings and other structures, is an essential sector of every economy (Hillebrandt, 2000; Su, Lin, & Wang, 2003). Construction, driving other interdependent sectors, and having a significant impact of the quality of life of the population, is typically considered a leading sector of an economy (Forbes & Ahmed, 2011; Su et al., 2003). There are a number of unique aspects of the sector, which reflect its importance. Firstly, the construction sector is vital for growth. The sector is closely associated with socio-economic development providing residential, commercial, and industrial spaces (Ofori, 2012). In relation to residential spaces, the activities of construction provide people with shelter, security, and protection from environmental and climatic hazards (Ofori, 2012). In relation to commercial and industrial spaces, the construction sector provides a significant proportion of the infrastructure that is required for goods and services to be produced in an economy (Forbes & Ahmed, 2011). Thus the construction section underpins development across a broad range, if not all, industries. This development leads to employment and income.

The second aspect of the construction sector, which is of interest, is its size. The construction industry is one of the largest product-based industries in the world (Loushine, et al., 2006). In the United States, it is reported that the value of the volume of the industry is approximately $1 trillion per annum (Forbes & Ahmed, 2011). In Australia, expenditure on residential buildings alone in 2006 was reported to be more than $30.9 billion according to the Australia Bureau of Statistics (Mills et al., 2009). The size of the construction sector can also be appreciated through reflecting on its direct contribution to gross domestic product (GDP). In the majority of settings, the sector contributes between 5 and 10% of GDP (Lopes, 2012). For example, in the United States, the sector, new construction has been reported as accounting for up to 8% of GDP in relatively recent years (Forbes & Ahmed, 2011). In the United Kingdom, construction has been reported as responsible for 5.4% of the GDP according to the Department of Trade and Industry, (Delgado- Hernandez & Aspinwall, 2005; DTI, 2003). And again, in some settings, such as Australia, the sub-sector of residential construction alone has been reported as accounting for ≥3.8% of GDP (Mills et al, 2009).

Thirdly, the construction sector is typically a target for investors. It has been reported that investment in the construction industry can equate to approximately 10% of all global investment (The Construction Industry Development Board [CIDB], 2004). Investment in residential housing alone, a sector reliant on construction activities, accounts for between 2 and 8 % of GDP, up to 50% of accumulated wealth, and up to 40% of household expenditure (Badiane, 2001). This large size of the sector, and sectors reliant on the sector, such as real estate, highlight the potential of the construction industry to contribute to economic growth (Ofori, 2012). In fact, due to the construction sector’s potential to act as a macro-economic instrument, governments are typically the major investors. Governments being responsible, to a large extent, for the construction of airports, bridges, hospitals, irrigation systems, ports, roads, schools, water and power infrastructure are thus reliant on the construction sector to a great extent (Hillebrandt, 2000).

Governments can also vary the levels of their level spending into construction for the purposes of inducing desired changes in the economy. This has been carried out noticeably in Japan and Taiwan in recent decades (Su et al., 2003). For this reason, the construction sector is often referred to as “the balance wheel of the economy” or “an economic regulator” (Hillebrandt, 2000). The effects that additional central investment into construction can have on the economy are referred to “pull effects” which refer to expansion in the overall economy that occur after expansions in construction, and “push effects” which refer to the expansion of the overall economy before expansions in the construction (Su et al., 2003). In other words, not only does construction provides places for manufacture to occur, leading to “pull effects”, but it also requires products from the manufacture sector, leading to “push effects” (Ofori, 2012).

Construction is also a labour-intensive industry. This means that can be an important source of employment and distribution of wealth. In some settings, the construction industry employs as much as 10% of the labour force (Lopes, 2012). With over one million corporations operating in the construction sector worldwide and at least 10 million persons employed in these industries it is an important sector for human resources (Forbes & Ahmed, 2011). It is also an industry characterised by high fluctuations and employee turnover, which means that it is a context in which new employment is generated rapidly (Forbes & Ahmed, 2011).

Given the importance of construction with respect to the health and economic vitality of populations, it is critical that the sector is one, which incorporates technological advances and best practices (Ofori, 2012). The management of outcomes in this sector is also particularly important due to the substantial investment required and the high risks associated with construction failure (Loushine, et al., 2006).

Construction is typically divided into four sub-sectors. The two dominant sub-sectors and residential construction (accounting for approximately 30 - 35% of the industry), including the preparation and formation of single-family homes, multi-unit townhouses, high-rise units, and condominiums, and building construction (approximately 35 - 40 %) related to the construction of schools, hospitals, universities, and commercial malls, amongst other buildings (Halpin & Senior, 2010). The remaining two sub-sectors are typically smaller in proportion and include heavy engineering construction (approximately 20 - 25 %), involving dams, tunnels, airports, highways and ports, amongst other buildings and structures, and industrial construction (approximately 5 - 10%) which refers to the construction of petro-chemical plants, heavy manufacturing plants, and mills (Halpin & Senior, 2010). This research will focus generally on the residential sub-sector and in particular on structural concrete building. This sub-sector has been chosen due to its size, importance, and the propensity for the occurrence of defects.

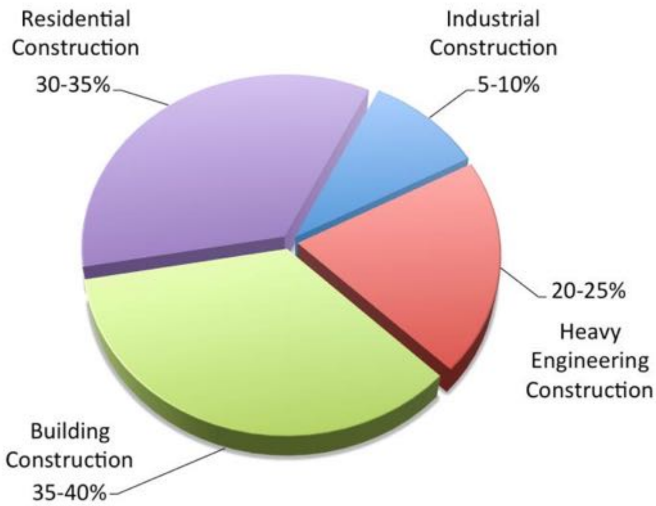


Figure 2.1 Breakdown of construction industry segments

The traditional approach to project delivery in the residential construction sector can be thought as having five stages. The first stage can be referred to as "project concepts" (Forbes & Ahmed, 2010). This is the initial stage and is the time that the owner conceptualises the project. The broad objectives of the project are contemplated and eventually planned, and the technical and economic feasibility of the project is considered (Meredith & Mantel, 2009). The second stage of project delivery can be referred to as the "preliminary design" (Forbes & Ahmed, 2010; Meredith & Mantel, 2009). This stage is a planning and design stage and concerns programming of concepts related to the intended use and size of particular spaces within the construction zone. This stage is characterised by the development of a scope of the project document, a preliminary budget, and a schedule. This is followed by "detailed design" (Meredith & Mantel, 2009). Between the second and third stages, engineering tasks will become more relevant and complete drawings and specifications will be made available. These documents and similar documents are then prepared in order to solicit bids from construction contractors.

The shift from the third stage to the four stages is signified by a transition from engineering to construction. This stage can be referred to as “construction” and involves the construction contractors given formal access to the site and contractual obligations commence (Forbes & Ahmed, 2010). This stage is also the time when sub-contractors may be engaged, and other matters of procurement of equipment, materials, and tools are finalised. The final stage is known as “start-up” and refers to the construction team conducting final inspections and the owner, through their agents typically, conducting inspections and owner acceptance and then the project turned over formally to the owner (Meredith & Mantel, 2009).

Errors in building have been found to arise primarily in the design and construction stages. For example, the United Kingdom's Building Research Establishment found that 50% of the errors occurred during the design phase and 40% of errors occurred during the construction phase (Building Research Establishment [BRE], 1982). Given that the design phase could include the three stages of “project concepts”, “preliminary design”, and “detailed design” as outlined previously, the suggestion is that of the five previously mentioned stages, the “construction” stage may be a dominant stage where actions lead to the occurrence of defects. This is supported by other studies such as Burati et al. (1992) who found that 78% of quality deviations are attributable to deviation from design specifications. In other words, poor adherence to design specifications in the “construction” stage was found to underpin departures from established requirements (Balson, Gray, & Xia, 2012). For these reasons, this research will focus on the “construction” stage of project delivery.

Construction as part of the project delivery, and in general, is an activity that is coordinated using hierarchical levels. As in other commercial areas, the first, or top hierarchical level is the “organizational” level in which the business structure and strategy is the core focus (Halpin & Senior, 2010). Legal matters and the various areas of functional management are also an important part of this level. Field managers will also be a focus on this level. The next subordinate hierarchical level is the “project” level. At this level, the focus is determining and organising resources for a specific project. Schedules are developed at this level (Whyte, 2014). Moving closer to labour onsite is the "operation" level. This level is also known as the "process" level and focuses on the field. At this level, identifying optimal processes, procedures, and protocols for construction is the target (Whyte, 2014). Also, at this level there is a focus on technology and the sequence of work tasks. Some taxonomies refer to the "process" level as the level which focuses on the sequence of work tasks, and they position this level under the "operation" level (Halpin & Senior, 2010).

The "task" level is the most discrete level. According to Halpin and Senior (2010) this level is concerned with "the identification and assignment of elemental portions of work to field units and work crews". The "task" level requires knowledge of fundamental field actions and work units. At this level, the focus is also on having knowledge and skill at the field crew member level (Whyte, 2014). The research project will focus on the "task" level investigating the anatomy of small manageable sub-tasks, and propose an analytical model to predict the occurrence of quality deviations and construction defects.

2.3 Definitions of the Quality Deviations and Construction Defects

There is arguably no general consensus in the construction literature concerning nomenclature for the description of unsatisfactory works (Sommerville, 2007). The range of interchangeable terms used in construction project management can complicate efforts to understand unsatisfactory performance (Love, 2002; Mills et al., 2009; Sommerville, 2007). Error, fault, failure, non-conferment, rework, deviation and defect are just some of the terms used to describe technical problems (Cheetham, 1973; Knocke, 1992; Love, 2002). This collection of terms, however, are not arguably not strictly synonymous each tending to indicate a different severity of problem and different for rectification (Mills et al., 2009). Thus, a lack of a more precise use of such terms underpins poor understanding of construction problems and compromises efforts to resolve performance issues (Mills et al., 2009). The upshot is that there is a need to delineate these terms so that their use more accurately represents the quality level of presented practices and output. The following paragraphs review these terms highlighting compatibilities and contradictions in their use.

A deviation is any "departure from established requirements" according to Burati and Farrington (1987). This definition is a broad one and does not in itself necessarily provide information on the need for rectification of a given issue. Burati and Farrington (1987) definition arguably implies that if the level of deviation is sufficient then rectification actions will be required depending on the context. Other definitions expressly state that a deviation is a departure from established requirements that is not so severe that rectification is required. For example, Davis et al. (1989) proposed that a deviation is a "result that does not fully conform to all specification requirements does not necessarily constitute an outright failure". Here, Davis et al. (1989) suggest that a deviation is a departure less severe than a departure from established requirements that would be necessary for a failure to have occurred. Deviation is a term that has been associated with manufacturing for some time. Some authors have used this custom to suggest that the use of the term should be limited to manufacturing (Burati et al., 1992; Farrington, 1987). However, at least since the use of formal building codes the concept of deviation, particularly as it related to tolerance, has become important to the construction sector (American Concrete Institute Code ACI-318).

A defect is "a deviation of a severity sufficient to require corrective action" according to Burati and Farrington (1987). This definition expressly provides that the deviation, that is, the departure from established requirements, must be so severe that rectification is mandatory. In other words, a defect is a departure from established requirements, which is unacceptable to the context. Georgiou et al. (1999) argued that defects could be divided into major and minor defects. With the former being any defect, which makes "the building unsafe, uninhabitable, or unusable for the purposes for which the building was designed or intended", and the latter occurring due to non-optimal performance of people, such as poor workmanship, or inappropriate material use, but importantly definitional, the latter not rendering the building uninhabitable or otherwise dangerous (Porteous, cited in Georgiou et al., 1999). The same authors argued that defects could be alternatively characterised in terms of their adverse impact on project cost and time. For example, those defects which cost more than $500 and/or more than 12 months for rectification actions would be considered major defects (Georgiou et al., 1999). Others place different emphases on the definition. For example, Atkinson (1987) suggested that a defect was “a shortfall in performance which manifests itself once the building is operational”. The focus of this definition is the late emergence of consequences as opposed to a significant departure from established requirements. Knocke (1992) and Mills et al. (2009) proposed definitions with similar conditions. With the first arguing that a defect was “the physical manifestation of an error or omission”, and the second, seeing a defect as “a tangible occurrence that can be rectified” (Knocke, 1992). Thus, there is a temporal difference with these types of definitions and that of Burati and Farrington (1987). While Atkinson (1987), Knocke (1992), and Mills et al. (2009) emphasize the need for the manifestation or consequence of the departure, in order for it to be classified a defect, Burati and Farrington (1987) arguably merely require the departure to require corrective action, and appear to not necessarily require evidence of manifestation of a consequence.

Failure is a term that is less commonly applied to the construction sector and more typically used with respect to the manufacturing sector. Atkinson (1987), however, referring to the construction industry, argues that a failure and a defect are not interchangeable concepts. According to this author a failure is “a departure from good practice, which may or may not be corrected before the building is handed over” (Atkinson, 1987). This can be contrasted with the author’s definition of a defect, which is again, “a shortfall in performance which manifests itself once the building is operational.” Thus, the author appears to focus on the manifestation of an issue once the building is operational with respect to defects however, failures are departures from good practice which may remain unknown or at least possibly uncorrected at the time of building handover. Ahzahar et al. (2011) used a simpler definition for the concept of failure interpreting it as “an unacceptable difference between expected and observed performance”. The expression “unacceptable” refers to the product condition or severity of risk. Arguably it is difficult to distinguish between concept of failure as defined by Ahzaher et al., (2001) with concept of defects as defined by Burati & Farrington, (1987). Other authors focus less on the difference between expected and observed performance in relation to tasks and products and focus more on a set of events that lead to unacceptable results. For example, Kaminetzky (1991) defined failure as involving any one or more of the following "a human act; omission of occurrence or performance; lack of success; nonperformance; insufficiency; loss of strength; and cessation of proper functioning or performance". Wardhana and Hadripriono (2003) definition of failure represents a more functional view of the concept stating it is "the incapacity of a constructed facility or its components to perform as specified in the design and construction requirements."

Error is another term that is often associated with the actions of humans. Busby (2001) defines an error as an occurrence which was "unexpected and which could not be attributed entirely to chance or circumstances". Thus, this definition focuses on the existence of an act or omission by a human, which caused the unexpected occurrence. The unexpected occurrence however is not caused, or at least not primarily caused, by chance. This is reflected in Reason and Hobbs (2003) definition of error, which shares similarities to Busby's and reads "the failure of planned actions to achieve their desired goal, where this occurs without some unforeseeable or chance intervention". For simplicity, errors could be thought of as human mistakes. This notion is expressed in Reason (1990) definition of errors, which reads "all those occasions on which a planned sequence of mental or physical activities did not follow as intended or if that sequence of plan could proceed, it still failed to achieve its desired outcome". Other definitions linked errors with poor human performance. For example, Hagen and Mays, (1981) defined errors as the "failure of the human to do a designated task within specified limits of exactness, sequence, or time". Errors can arise due to persons departing from established norms and standards of care. In this regard, errors may be negligent or even reckless. Knocke (1992) definition of an error within the construction sector is "any departure from correct construction (including checking and supervision) technical inspection; and absence of adequate instructions for maintenance and operation of the building".

Nonconformance is a term that appears to sit between deviation as defined by Burati and Farrington (1987) and defect as defined by the same authors. Nonconformance is arguably an operational term. For example, nonconformance is defined as "a deviation that occurs with a severity sufficient to consider rejection of the product, process, or service" (Burati & Farrington, 1987). The basis for rejection is the departure from established, or agreed upon, requirements. This is reflected in definition of the term by Battikha (2008) considers that "non-conformance occurs when the finished state of a project and/or its components deviates from established requirements and necessitates decisions to be made regarding their acceptance and/or rectification." Thus, nonconformance is a term closely tied into quality management. In the ISO 9000:2005 Quality management systems - Fundamentals and vocabulary publication, nonconformance is defined as the "non-fulfilment of a requirement", where that requirement is "expression in the content of a document conveying criteria to be fulfilled if compliance with the document is to be claimed and from which no deviation is permitted" (ISO 9000: 2005). Thus, the term noncompliance tends to have contractual connotations as opposed to functional connotations. For example, as Burati and Farrington (1987) argue, "In some situations the product, process, or service may be accepted as is; in other situations it will require corrective action." Thus, noncompliance is related to agreed upon conditions of quality as opposed to the consequences or manifestations of such as departures.

The definitions promoted by Burati and Farrington (1987) and ISO 9000:2005 provide the most convenient conceptual framework to to further explore the concept of quality deviations and construction defects for the purposes of this research project. For Burati and Farrington (1987), a deviation is "a departure from established requirements", whereas a defect is more significant event in itself being "a deviation of a severity sufficient to require corrective action". The point of distinction is thus whether the departure is such that corrective action is mandated. Where no rectification action is required the occurrence will be a deviation where actions is mandated then it will be a defect. This research project will also use the concept of nonconformance as per ISO 9000:2005, namely, the "non-fulfilment of a requirement", where requirement is "expression in the content of a document conveying criteria to be fulfilled if compliance with the document is to be claimed and from which no deviation is permitted".

As mentioned, to date, quality deviations and defects in construction industry impact significantly on the overall profitability and viability of the construction sector. Preventing and reducing the quantum of quality deviations and defects in this sector will mitigate the adverse consequences of additional cost and time overruns.

Isolating specific definitions for deviation, defect, and nonconformance, is an important starting point for a more in-depth and appropriate investigation into the quantity and nature of these departures in relation to construction. The dimensions of causes and sub-causes of these departures need to be better understood. Further, the interaction between causes and specific construction tasks also needs to be better understood. To date, there have been few studies that have reported on the relationship between deviation/defects, the nature of construction tasks, that is, the specific task characteristics, and task-related factors, such as the task resources and surrounding environment.

2.4 Quality Deviations

2.4.1 Overview of quality management practices in construction

Quality is the "degree to which a set of inherent characteristics fulfils requirements" according to the ISO 9000:2008. Despite this often taken for granted definition, the term is used broadly. For example, the concept is often used differently in different contexts. It can be used to refer to a standard, or a characteristic of something. The commercial use of the term in marketing has further expanded understandings of its meaning(s) (Djebarni & Al-Abed, 1998). Thus, arguably for the most part there is often a lack of awareness of the precise meaning of the concept, and there is no general consensus on which definition should be used when measuring construction quality (Djebarni & Al-Abed, 1998).

Having said this, Mpambane (2008) argue that while quality is interpreted broadly and with some inconsistencies, overall, issues related to quality, from the provider's perspective each affect profitability and business viability. The author argue that a conception of quality that considers its affect on the bottom line can have advantages as principals are able to appreciate the impact that quality issues have on client satisfaction and business reputation (Mpambane, 2008). The author, also argue that it is important that the management of quality is not merely seen ensuring a "degree of excellence" or "gold-plating", and that in fact, the management of quality is a critical part of commercial risk management. It is commented that the management of quality with respect to commercial housing construction involves expenditure of at least 1% of total project cost (Mpambane, 2008).

Quality management is designed to ensure that business practices meet the needs of clients and other stakeholders, such as policy makers who will enforce statutory and regulatory requirements related to the products or services (ISO 9000: 2008). However, it is also helpful to conceptualize quality management as essentially the prevention of deviation. Whether quality management interventions are client-focused or product-focused, preventing departure from established requirements will generally underpin high quality. In other words, where defects are present, the implication is an absence of quality, and the consequence is at least dissatisfaction, and in the context of construction, potentially life-threatening structures (Shammas-Tomma, et al., 1998).

Quality management is, thus, concerned with achieving high quality, which, in other words, simply refers to fulfilling client requirements whether those requirements are instructional or functional (Evans & Lindsay, 2008). For a long time, proponents in the construction industry have struggle to consistently achieve high quality outcomes. Residential building projects, an important sub-sector of construction, are often characterised by excessive resource inputs and less than optimal end products (Mpambane, 2008). Kazaz et al. (2005) note that the situation is markedly worse with respect to the construction of large scale housing products targeted at low and middle-income deomographics.

The earliest well-known quality management interventions were arguably linked to what is now known as scientific management. Taylorism is the name that is used to refer to a type of management in which the tasks or processes in a business or activity are divided up into micro-tasks (Boxall & Macky, 2009). In other words, it is a type of quality management concerned with understanding workflows (Boxall & Macky, 2009). Taylorism gains its name from one of its founders, Frederick Taylor, who together with his firm promoting the approach to management calling it scientific management. The practice was popular between 1900 and 1920 (Alder, 2007). It involved first-line supervisors and operational level managers ceding authority and power to more senior managers, and tasks and quality requirements being expressly prescribed (Alder, 2007). Taylorism is known as being a quality management strategy of high intensification and low involvement (Boxall & Macky, 2009).

Outside of construction, Henry Ford and Karl Friedrich Benz were making important gains in productivity and commercial success through adopting quality management strategies to production lines for automobiles (Dietsche & Kuhlgatz, 2015). After this time, Walter Shewhart proposed an important quality management technique known statistical process control through measuring day-to-day productivity (Mawson, 1993). This technique has been largely adopted to the manufacture sectors however, its application in the construction sector has been supported by a number of researchers. Crosby (1979), Juran (1981) and Deming (1986) each made important contributions to the understanding of quality management. Crosby (1979) argued that quality improvement was a crucial tool for process cost reduction. He advised that high quality outcomes where important for not only high-end products but also low-end products. Juran (1981), shortly after, developed quality management framework, which involved three stages of activities, namely, quality planning, quality control, and quality improvement. Juran (1981), as Stewhart earlier, emphasized the advantages of using statistical tools as an approach to eliminate defects. Deming (1986) famously argued the relevance of organisation behaviour and quality management. The philosopher developed a framework, which emphasizes the importance of leadership, the systemic nature of organizations, and a need to reduce and prevent deviation in organizational processes (Dean & Bowen, 1994).

The work of these previous proponents, including Crosby (1979), Juran (1981) and Deming (1986) led to the development of key principles in quality management, these principles being that customer focus is required, improvement must be continuous, and that teamwork is essential. The development of these key principles led to the promotion of the total quality management (TQM) approach to quality management (Loushine, et al., 2006). TQM is a well-known approach to quality management in the construction sector. TQM is said to have arisen in popularity as a result of competitive pressures facing firms such as increased accountability concerning project quality (Abdelsalam & Gad, 2009). TQM has been reported to be a suitable approach to manage quality in the construction sector due to the industry's complexity. As Abu Baker & Onyeizu (2011) note TQM “has proved to be a useful tool in ensuring the achievement of set standard and successful productivity improvements in the construction industry."

Continuous improvement (CI) is another approach to quality management. One of common undercurrents of TQM and CI is the use of measurement. The well-known quality management saying is that if it is not measurable, it is not manageable (Abdelsalam & Gad, 2009; Feigenbaum, 1990). Some authors have noted that the nature of CI as a quality management approach means that it can face significant resistance from top management due to the emphasis on organisational renewal. Savolainen (1999) notes CI practices "imply a challenge to management: the progress in developing CI capabilities is embedded in a rooted managerial ideology through which inimitable competitive advantages can be realized."

Prevention, appraisal and failure (PAF) is another quality management approach which is recently began used in the construction sector (Abdelsalam & Gad, 2009). The PAF method is based around a set of assumptions. The first assumption is that investment in prevention and appraisal activities reduces the cost of failures. The second assumption is that additional investment towards prevention activities will reduce the cost of appraisal activities (Juran & Gryna, 1993). The PAF approach is therefore interested in four categories of non-compliance costs. The first category refers to any costs associated with the prevention of failure (Tsai, 1998). This includes the cost of appropriate employee recruitment and selection, employee induction, training and development, and the study of processes. Collectively, these are known as prevention costs. The second category refers to costs incurred in an effort to prevent nonconforming products from being dispatched, shipped, or otherwise used (Tsai, 1998). These costs may be assessment costs, accreditation costs, grading costs and other related costs. The third and fourth categories refer to costs that are incurred once the nonconformance has already been recognised. The third category refers to costs that are arise internally prior to delivery (Tsai, 1998). These include the costs due to the reworking of defective components, costs of scrapping, and the costs of contractual breaches arising from delivery delay. The fourth category refers to costs that arise externally after delivery and include matters of compensation in the case of defective products, as well as the cost of repairs and dealing with client complaints (Tsai, 1998). The cost of lost business arising from client dissatisfaction should also be included in this category.

Quality assurance (QA) is another quality management intervention that is applied in construction projects. The International Organization for Standardization (ISO) 9000 family advocates the use of QA interventions for the purposes of better ensuring that on-paper requirements and specifications are met (Delgado- Hernandez & Aspinwall, 2005; Pheng, 1993). QA as a quality management intervention is based on the assumption that there is risk involved in any construction project. QA, based on the ISO 9000 guidelines, involves the research, formulation, and promotion of a complex collection of procedural documents (Chelson, 2010). However, the application of the QA approach to quality management in construction is challenged by some of the typical conditions in construction, such as high employee turnover and high complexity (Bubshait & Al-Atiq, 1999). These will be discussed further in section 2.4.2.

Quality control (QC) is another approach to quality management in construction. Demarcation of QA and QC can be challenging however, it is generally accepted that quality assurance tends to refer more to instrumental quality whereas quality control refers more to the quality of personnel (Abdul-Rahman, 1995; Sinha, Harrington, Voehl & Wiggin, 2012; Whyte, 2014). QC can involve the use of an inspector (Satterfield, 2005). QC is usually focused on ensuring conformance to original and approved planning decisions and designs (Toh, 2006).

Building codes have been increasingly used and promoted in the construction sector since at least 1963 (Poston & Dolan 2008). As a quality management device, building codes help to make explicit statutory and regulatory requirements (Love, et al., 2013). Over time, building and engineering standards have been modified based on stakeholder feedback and improved in many countries such as Australia, United Kingdom (UK), United States (US) and Singapore (Love, et al., 2013).

Quality management practices applied in the construction have been found to attain a number of benefits. For example, demonstrable evidence of cost benefits has been reported in studies. The United Kingdom's Building Research Establishment has estimated that eliminating rework, a goal of quality management in construction, would result in at least a 15% saving on total construction costs (Building Research

Establishment [BRE], 1982; Love & Edwards, 2004b). Barclay Construction corporation in Australia reported that pre-quality management intervention their rework costs were approximately 5% of contract value, however, post-quality management intervention these costs were roughly 1%. For this entity, the reduction in rework led to cost savings of $4.2 million (Lomas, 1996). Construction Industry Development Agency [CIDA] (1995) reported similar reductions in proportion of rework as a result of introducing quality management interventions. Prior to the adoption of quality interventions, the average rework proportion was 6.5% of contract value, however, post-intervention, the average cost was 0.72%. Tucker et al. (1996) and Love et al. (1999) reported similar findings.

Quality management interventions in the construction sector has also been reported as leading to less direct cost savings such as a reduction in occupational health and safety related expenditure. In a recent study by Wanberg et al. (2013) it was found that defects underpinned as much as 60% of safety issues in the construction sector and that there was a significant relationship between quality and safety. Also recently, Borg and Song (2014) argued that there was a statistically significant relationship between quality and productivity noting that quality management interventions not only increased incidence of desirable quality but also led to cost savings due to increased productivity. Others such as Naoum and Behbehani (2005) argue that given the close nexus between quality and the achievement of customer satisfaction in competitive markets, such as the housing projects market, quality is often the principal differentiating factor, and therefore represents an important competitive advantage.

2.4.2 Barriers to adoption of quality management in construction industry

While quality management interventions do appear to be increasingly applied in construction projects, particularly larger projects, barriers to the uptake of these methods and techniques exist. Despite potentially dramatic benefits, resistance still exists as proponents in the construction sector perceive that quality management tools and techniques require substantial investment (Bubshait & Al-Atiq, 1999; Tchidi, He, & Li, 2012; Turk, 2006). Poorly developed or superficial quality management interventions, such as quality assurance based on post-production, have also contributed to some negative views towards such interventions in the construction sector according to Jaafari (1996). Other financial, practical, and perception constraints are also reported to underpin slow adoption of quality management interventions in some settings (Delgado- Hernandez, & Aspinwall, 2005; Irani & Holt, 2000; Jaafari, 1996; Love, Li, Tchidi, He, & Li, 2012). The upshot of slow adoption is the continuation of sub-optimal and dangerous practices on construction sites.

As mentioned, TQM is a quality management intervention and philosophy that is aimed at improving the organisation's likelihood of fulfilling requirements (Delgado- Hernandez, & Aspinwall, 2005; McIntyre & Kirschenman, 2000; Polat, Tatar, & Damci, 2011). However, a number of barriers to the adoption of TQM in the construction sector have been identified in the literature. One category of barriers arise from the conservative nature of the construction sector in that managers are not eager to move away from established conventional practices. In fact, in a study of 120 contractors in Turkey, "lack of top management commitment", "lack of top management support", and "lack of top management leadership" were found to be the top three barriers to TQM from a selection of 18 barriers (Polat et al. 2011). Prevailing organisational culture in the construction sector can be another barrier to TQM. The philosophy is that not only should the quality of products be in issue but in fact the quality of all issues within the organisation (Polat et al. 2011). The reactive and short-term nature of the construction industry and the focus on one-off complex projects has been identified as a condition not conducive to the adoption of TQM.

Haupt et al., (2004) investigated barriers to the implementation of TQM and found that high turnover of construction employees, difficulties in measuring outcomes of TQM and doubts concerning the relevance of the intervention to construction were significant obstacles. The researchers also noted that the construction industry typically involved a high proportion of sub-contractors and these parties were more often than not disinterested with principal company quality interventions (Haupt et al., 2004). Another example, low bid-subcontracting is another established practice is that construction companies typically practice (Harrington, Voehl & Wiggin, 2012). It is often reported that clients in the construction sector are heavily price sensitive placing emphasis on engaging a contractor with the lowest overall price (Harrington, et al., 2012). This focus can lead to a situation where reputation for quality, past experience, and current workload are overlooked as selection criteria. The consequence of this can be that contractors seek to make heavy cost cuts and are reluctant to invest in activities, which they perceive are not directly related to completing the project (Harrington, et al., 2012).

QA, based on the ISO 9000 guidelines, as mentioned, involves the research and formulation of complex collection of procedural documents. The goal is that members of the organisation will follow the directions providing in this collection of protocol and procedure related content, and that as a result there will be an improvement in quality (Auchterlounie, 2009). Construction companies reportedly struggle to implement QA in some instances due to the documentation and assessment requirements (Auchterlounie, 2009; Delgado- Hernandez & Aspinwall, 2005). Some commentators have noted that QA is often perceived as "pervasive" and/or "daunting" by proponents in the construction sector (Chelson, 2010).

Superficial adoption of QA is reportedly undermining the effective use of the intervention. While ISO 9000 has attracted a good reputation and positive client reactions in most settings, researchers have observed a tendency for contractors and subcontractors to "pay lip service" to QA (Love & Edwards, 2004a). In other words, QA is only implemented through the words of these principals, but it is not being implemented in substance. This issue is potentially likely to be related to the barrier found in relation to TQM that low bid subcontracting leads to a situation where quality may be neglected while cost savings are reveled (Haupt et al., 2004). It has also been suggested that the perceived increased administrative workload is also a reason underpinning superficial adoption (Love et al., 1999; Tucker et al., 1996).

Lengthy time and high cost requirements to adoption were also identified as barriers to QA implemention (Turk, 2006). The ISO 9000 certification process has been found to be one with onerous obligations. One of the issues is that the ISO 9000 approach involves a standardised approach to a wide range of quality elements. Bubshait and Al-Atiq (1999) note "ISO 9000 consultants look at all quality elements in the same way." The problem is that in the construction sector some quality elements are more pressing or more immediately important. Thus, authors recommend that the prioritization of quality elements relevant to the specific construction context may be helpful.

As mentioned, QC is also an important quality management intervention. As mentioned, QC typically involves inspection of processes and products to detect any deviations from requirements (Kakitahi, et al., 2011). However, barriers to the adoption of successful QC in the construction sector also exist (Jafari & Love, 2013). For example, the United Kingdom's Building Research Establishment noted that participants in the QC process are often not sufficiently motivated to carry out the QC task appropriately or in good faith (Love & Edwards, 2004b). They also found that time, onsite, for QC is usually scarce. They noted that the results of QC events were not usually factored into contractual arrangements. And amongst others, they also noted that designers tended not to provide sufficient information for contractors to be able to achieve high quality (Love & Edwards, 2004b).

Overall, a barrier to perhaps all of the quality management interventions is a perception that the costs will not be justified. Some studies have indicated the cost of supervisory activities can be as high as more than 6% of total project cost (Jafari & Love, 2013). For example, Dolan and Schuler (1987), found that the cost of onsite supervisory personnel alone could be in excess of 3% of total project cost. Chen et al. (2008), similarly, found that cost of onsite supervisory activities could vary from 0.6 to 6.1% of total project cost (Jafari & Love, 2013).

2.4.3 Analytical reasoning and quality management

Analytical reasoning refers to use of deduction, top-down logic, and induction, bottom-up logic, to come to conclusions about premises/representations that are made available (Patokorpi, 2006). The connotation of the phrase is that additional thought-processes are required, and not only is information seen in the context of a problem, it is also considered in the context of finding a solution to the problem (Cox & Thompson, 1997; Patokorpi, 2006). The process of construction requires inputs, not limited to, human resources, know-how, management, materials, tools, and favourable environmental conditions. In short, it is a challenging task to determine what events or conditions have led to a particular quality issue and what approaches may be helpful to improve the situation (Tchidi, He, & Li, 2012). This task of understanding causation is also complicated by matters prior to construction such as design, regulatory matters such as building codes, and other confounders leading to quality deviation (Cheng & Li, 2015). Yet while the importance of determining causation and factors that contribute to quality deviation is an acknowledged issue for proponents in the construction industry, particular due to the high cost of rectification actions and their related consequences including cost and time overruns and exposed to claims for damages, the quest to improve quality management interventions has arguably lacked enthusiasm (Love & Edwards, 2004a; McIntyre & Kirschenman, 2000; Polat, Damci & Tatar, 2011; Tchidi, He, & Li, 2012).

Thus, despite the complexity of the construction industry, authors believe there is insufficient sophistication used in prevailing quality management interventions, primarily due to a lack of analytical reasoning (Cheng & Li, 2015; Tchidi, He, & Li, 2012). For example, Tan and Abdul Rahman (2011) argued that experiments, inspections and other traditional quality management techniques continue to be relied upon by the majority of proponents in the construction sector do not offer insight into the mechanisms, organisational behaviours, and conditions that lead to deviation, and therefore offer limited practical value. Bubshait and Al-Atiq (1999) argued that experiments, inspections and other traditional quality management techniques only offer construction companies "elements" of a quality management system, and without interventions that inspire further analytical reasoning, are, as noted more recently by Tan and Abdul Rahman (2011), limited in value.

Noting the issue, Al-Tmeemy, Abdul Rahman, and Harun (2012) reflecting on issues with low value quality management interventions, conducted a study on increasing concerns with respect to a lack of what they referred to as "optimized quality solutions" in the construction sector. The authors argued that current research in quality management in construction was limited, and that "construction practitioners do not yet have the basis for optimizing quality efforts and resources" (Al-Tmeemy et al., 2012). The authors proposed that an "optimized quality solution" would require (1) systematic identification of factors affecting quality, (2) analysis and quantification of the importance of each of these factors, (3) identification and quantification of interventions to improve quality, such as increased inspections, audits, and review, or increased control over the supply chain, and (4) a final assessment of feasibility and optimisation. One of the strengths of Al-Tmeeny et al. (2012) appears that their framework focuses on the quantification identification of factors and solutions. In line, Aljassmi & Han (2012) in a recent study concluded that aspirations to optimise resources for quality management in construction should focus on specific quality improvements, such as the reduction of defects, in order for any optimum solution to be possible.

The suggestion is that measurement is necessary to encourage analytical reasoning and enhance the value of quality management interventions. The need for measurement systems is increasingly being acknowledged (Aljassmi, Han & Davis, 2013). Some modern quality management interventions puts emphasis on the measurement of indicators of quality throughout the production process and not merely with respect to the final product processes (Tchidi, He, & Li, 2012). Other authors have noted that there is a lack of adoption of quality management interventions that are focused on the analysis of defects. For example, Cheng & Li, (2015) noted that traditional quantitative analytical methods, which respect to defects tended to not be useful for the purposes of identifying direct and indirect causes. The same authors also noted that there was limited opportunity for proponents in the construction sector to review databases about defects, as the development of such resources had been neglected thus far.

Others have noted a need for more research towards developing an effective defect management model. For example, Cheng & Li, (2015) believe that measurement and analytical reasoning is required to isolate and assess key factors causing defects, and the relationships between these factors, so that operatives are better positioned to control relevant factors and reduce defects. The emphasis on relationships and interconnections between factors is supported by systems-approach theorists, and authors in the project construction field who note that such projects are “tightly coupled systems”, where events happening in one sphere of the system are often likely to trigger or exacerbate events in other spheres (Perrow, 1984). In line, some authors argue that factors must be tracked so that system pathways and conditions leading to quality success or failure can be understood (Aljassmi, Han & Davis, 2013; Cheng & Li, 2015).

Given that some have argued that a lack of analytical reasoning undermines the value of traditional quality management interventions, it is important to review some of the trends with respect to this in the construction industry. Traditionally, risk analysis has assumed the dominant position in quality interventions (Tah & Carr, 2000). Quantitative risk analysis derived from estimating probabilities and probability distributions for time and conventional cost analysis have been popular techniques (Sato, Kitazume, & Miyamoto, 2005). However, the limitation of these approaches has been a neglect of qualitative features of the circumstances which may be significant and reliance on subjective inputs. This methodological issues have lead researchers to move towards approaches which feature risk quantification and risk modeling (Tah & Carr, 2000). These approaches, particularly the latter, are reported as suitable vehicles for the promotion of communication, effective teamwork and risk-response planning.

Other approaches include defect analysis, which typically focuses on using statistical techniques to isolate relevant design, environment, materials, craftsmanship, and maintenance factors (Chong, & Low, 2005; Rounce, 1998). The approaches to defect analysis that have been conducted so far have generally reported two limitations (Cheng & Li, 2015). The first is that researchers report that it has been difficult to develop models and propose hypotheses in investigations where data on defects is large. The second is that the causation of defects is usually characterised by multiple factors. As a combination of two or more determinants are believed to underpin the causation of defects, it is considered that even after traditional defect analysis methods have been used, particular patterns or phenomena of causation may be hidden (Cheng & Li, 2015).

The next section reviews the literature of the factors and causes of the deviation and defects in construction industry, and further highlights the industry need for developing an anatomy analytical understanding of the micro-level of the task (i.e., sub-tasks or sub-task requirements) in order to measure its sensitivity towards the quality deviation and construction defects as well as identify which factors that have most influence toward the deviations and defects.

2.5 Construction Defects

2.5.1 Defects causes

While investigations derived from a quality management approach have been used to identify, reduce and prevent defects, the occurrence of these deviations in construction is still universal (Love, Lopez & Edwards, 2013; Turk, 2006). The occurrence of defects in the construction sector has been described as "an inevitable and entrenched" phenomenon underpinned by a general lack of supervisory attention (Sommerville, 2007). The peculiarity of the situation is that while analysts report insufficient management of defect proliferation, these deviations can have a wide-scale impact on the success of construction projects (Busby & Hughes, 2004).

A typical approach to understanding defect occurrence is to analyse their causation (Busby & Hughes, 2004). As mentioned, authors have attempted to achieve this in different ways, however, one of the more recommendable approaches, has been to trace defects back to the latent conditions in the project responsible for generating such error. Authors refer to these latent conditions as "pathogens", and argue that they exist within projects incubating until they become distinct actual failures. The Building Research Establishment (Building Research Establishment [BRE], 1982) found that up to 90% of defects were caused by latent conditions. Other researchers have reported that a lack of awareness of potential adverse latent conditions tends to exacerbate pre-existing issues such as project miscommunication (Al-Hammad, Assaf & Al-Shihah, 1997). Including latent conditions and defects on the agenda for pre-contractual discussions has been recommended by some analysts as a means to increase awareness of the need to eradicate defects (Davey et al., 2006; Huovila et al., 1997). Underpinning such discussions on project conditions and defect prevention and reduction is knowledge of defect systems.

Pena-Mora et al. (2003) argued that defects are usually caused by latent conditions related to organisational operational issues and/or uncertainty. With respect to organisational operational issues, it is argued by latent conditions can be attributable to people, process and project structures. For example, construction is a sector, which relies on different departmental experts and extensive sub-constructing. When these different groups of persons contribute towards the planning and execution of a construction project, there is a significant risk of interference (Pena-Mora et al., 2003). As the project moves from stage to stage, the risk of interference can be increased. Thus, as it has been argued that conflict is inherent in organisations, some researchers argue that the occurrence of defects will then be inherent (Meredith & Mantel, 2009). With respect to uncertainty, the authors argue that the complexity and scope of construction projects typically means that there are a number of variables outside the immediate control of the project manager, which generate potentially adverse latent conditions (Pena-Mora et al., 2003).

The reference to uncertainty also reflects a risk probability approach to defect analysis that some analysts have used (Reason, 1990; Tah & Carr, 2000). For example, due to a perceived relationship between uncertainty levels and the reactions of personnel, one approach has been to predict how employees would be likely to respond to given construction environments and any latent conditions that may exist (Reason, 1990). This approach was referred to as “predictable errors”, and was based on the assumption that managers would be able to predict the behaviour of personnel with respect to a sequence of conditions (Busby & Hughes, 2004). It was also argued that this approach could be used to develop sequence of actions for personnel to follow so that unwanted, defect causing actions, could be eradicated (Aljassmi, Han & Davis, 2013; Love, Edwards, Irani & Walker, 2009; Reason, 1990)

The nomenclature has not been limited to latent conditions and pathogens. Almost interchangeable terms include “origin causes” and “root causes” (Josephson & Hammarlund, 1999; Sommerville, 2007). The latter term of “root causes” is often used in conjunction with “causes” or “direct causes”. The terms are differentiated based on their proximity to the erroneous action. While a root cause may take on the appearance of an undesirable condition that on own its has any negative consequence hidden, a “cause” will be direct, identifiable, and provable (Love, Edwards, Irani & Walker, 2009). This will be described more following in Section 2.5.2.1. To understand this more it is convenient to review these positions of these concepts in relation to the series of construction defect events model proposed by Brunsson (1985, cited in Josephson & Hammarlund, 1999). The author argued that the phenomenon of defects could be best understood as a series of events. The first being "causes". These "cause(s)" would led to "erroneous action(s)" which would subsequently led to "manifest defect(s)" and related "consequences". Consistent with the definition that defects need rectification action, the final stage of the model, following from "consequences", is "corrective measures" (Brunsson, 1985, cited in Josephson & Hammarlund, 1999). This is shown in the following figure, Figure 2.2.

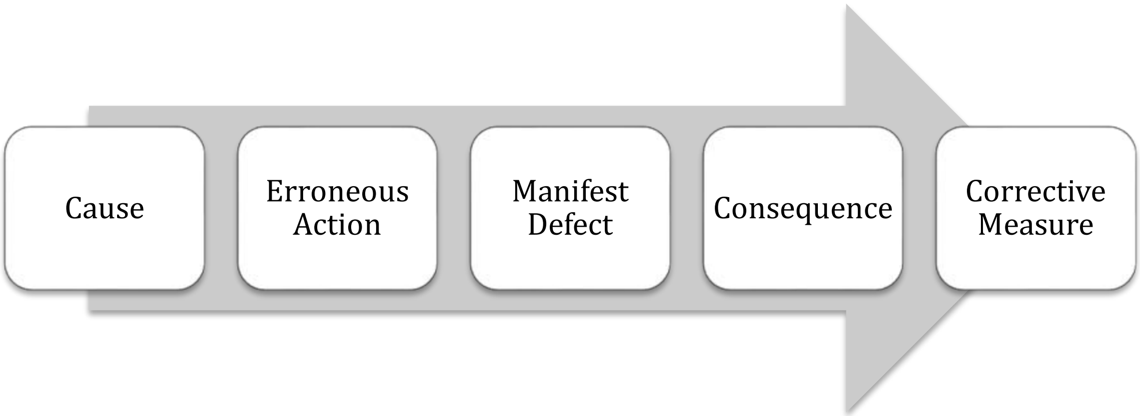


Figure 2.2 A series of construction defect events
(Source: Brunsson, 1985, cited in Josephson &Hammarlund, 1999)

While in the previous figure (Figure 2.2), "causes" is referred to as one stage, it has become more popular, and/or it is arguably more accurate to differentiate root causes from direct causes (Busby & Hughes, 2004; Sommerville, 2007). While a starting point then may be a recognition that root causes should be distinguished from direct causes, it is argued that there is a great deal of research required to better understand the origins of defects (Sommerville, 2007). Firstly, as Sommerville (2007) argue the origins of defects, that is, the root causes, are "inextricably linked" to the "causes" and it can be difficult to discern the two. Moreover, there are typically multiple root causes each with different relative strengths that eventually led to defects. Additionally the genesis of sources of defects is not typically agreed upon which can further complicate comprehensions of the origins of defects. Love, et al., (2009) and Aljassmi, et al., (2013) investigated root causes of defects as part of their study on rework pathways. The following figure, Figure 2.3, reveals potential root causes that could contribute to a "cause", "flawed action", "manifest defect", "consequence" and eventual "corrective action" (Sommerville, 2007).

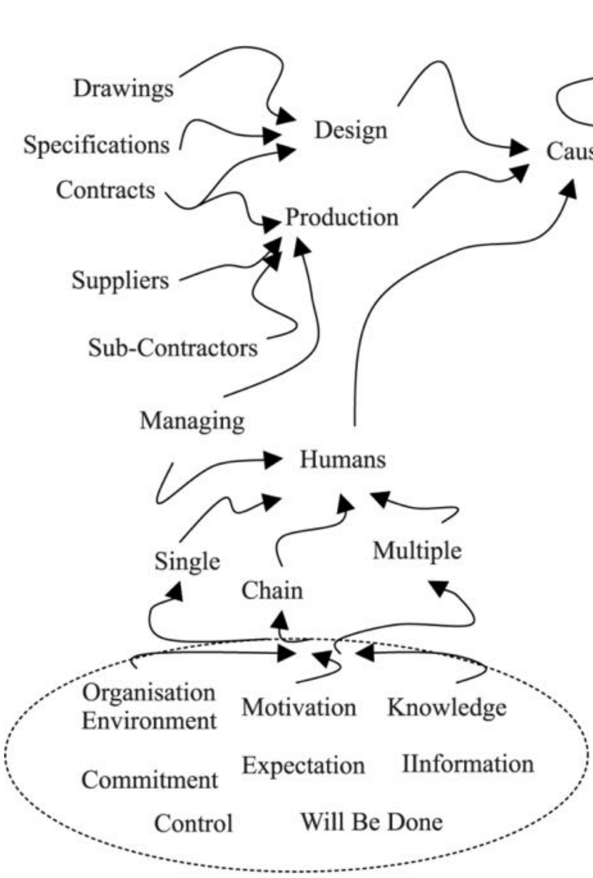


Figure 2.3 The multiplex rework pathway (Source: Sommerville, 2007)

2.5.1.1 Causes of defects

A "cause" in general a term is "something that brings about an effect" (Merriam-Webster, 2012). From a construction perspective, a "cause" can be operationally defined as "a proven reason for the existence of a defect" (Gryna, cited in Juran, & Gryna, 1988). For the purposes of this research the concept of cause will be divided into root causes and direct causes, and will be discussed following.

2.5.1.1.1 Root causes (Origins causes – Latent conditions)

As mentioned, root causes, also known as latent conditions, origin causes, or pathogens, are those conditions that are typically hidden but can contribute to the occurrence of a defect (Busby and Hughes 2004). Root causes have been referred to as "the most basic reason for an undesirable condition" (Josephson & Hammarlund, 1999). Traditional construction projects by their nature are highly prone to conditions and acts that can lead to defects (Tan & Abdul Rahman, 2011; Tchidi, He & Li, 2012). This is due to a number of conditions inherent to the industry, such as its complexity, its fluctuations in supply and demand, one-off projects, high dependence of sub-contracting, and rapid employee turnover. These conditions, and others, have been repeatedly found to underpin the proliferation of error and construction failure (Love et al. 2009). It has been argued that deviation can better understood and therefore managed through viewing occurrence of defects in the construction setting as a phenomenon similar to the onset of disease in living organisms. Busby and Hughes (2004) use this analogy and use the term "pathogens" to the refer to root causes of construction defects. Similarly, authors note how "pathogens" in this sense are able to contribute to the breakdown of complex technical systems (Reason 1990). One of the advantages of this view of root causes is that it highlights that within project systems exist areas of vulnerability and where these conditions form aggregates there can be a high risk of defects (Aljassmi, et al., 2013; Sommerville, 2007).

Busby and Hughes (2004), using the nomenclature of "pathogens" has argued that three categories exist, namely "organisation pathogens" which arise from the operation or structure of the organisation, "system pathogens" which arise from the system(s) of the organisation, and "industry pathogens" which arise from the regulatory and structural aspects of the industry. An example of an "organisation pathogen", that is one that relates to the operation of the organisation, according to Busby and Hughes (2004), could be poor information exchange leading to tentative assumptions and delay in task onset. A "system pathogen" example that is relating to the systems could be reliance on obsolete engineering information due to change control system latency. Finally, a "industry pathogen" example could be mandatory government/central contracting regulations leading the firm to deal with contractors whom they have never dealt with before (Busby and Hughes, 2004). Others have considered the theoretical relationship between root causes and other constructs relevant to construction. For example, Tah and Carr (2000) investigated defects as part of their study of risks in the construction sector. Specifically, the pair sought to establish a hierarchical relationship between risks, however, in doing so their findings also revealed information about pathways of defect causation within construction. Tah and Carr (2000) argued that risks could be divided into internal risks and external risks. Internal risks were divided into local and global risks. The local risks included labour, plant, sub-contractor, materials, a site. Arguably these internal local risks provide a good indication of source of direct causes of defects in construction (Tah and Carr, 2000). It is likely that the proven reason(s) for the existence of a defect could be isolated from this group of risks.

In contrast, the global risks that Tah and Carr (2000) refer to including client, contractual, design, management, location, timeframe, financial, amongst others arguably more accurately reflect root causes in that they appear to be more latent and more likely to indirectly contribute to defects. Similarly, the external risks that the pair refer to including technical change, physical, political, and economic matters not internal to the project also appear to be consistent with root causes of defects (Tah and Carr, 2000). Thus, while the following figure, Figure 2.4, shows Hierarchical Risk Breakdown Structure ('HRBS') arguably it could also be useful for providing a suggestion of the topology of root causes and direct causes of defects in construction (Tah and Carr, 2000).

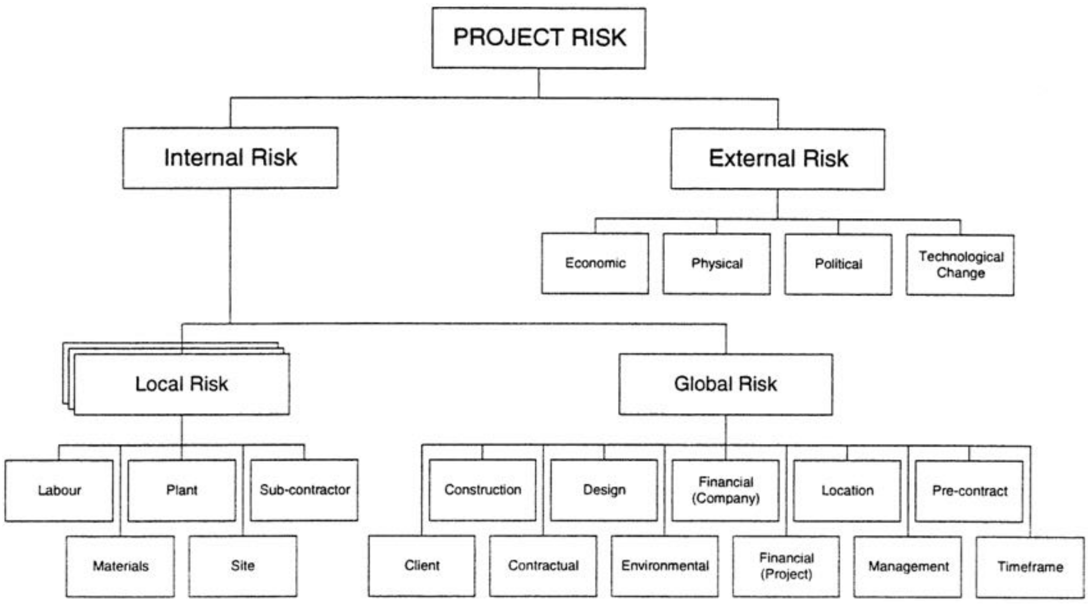


Figure 2.4 The Hierarchical Risk Breakdown Structure (Source: Tah and Carr, 2000).

The vast majority of adverse events that can occur in construction typically are attributed to departures from established requirements whether they be technical, supervisory, regulatory or otherwise (Georgiou, 2010). Josephson & Hammarlund (1999) concluded that root causes were "difficult to identify" but nonetheless could include cost pressure, time pressure, client project control, instability, inexperience, lack of top management support amongst others.

Thus, arguably one difference between root causes and direct causes is the extent that they can be rapidly identified (Sommerville, 2007). The former may be particularly difficult to isolate. Root causes essentially as latent conditions, will lay dormant until the manifestation of a defect. Personnel will typically remain unaware of the adverse consequences of particular decisions that are made with respect to the project (Aljassmi, et al., 2013). In other words, the significance of particular vulnerabilities is unclear until actual failure occurs (Busby and Hughes, 2004). Often root causes will lay dormant because of a system defense, such as managerial precaution. However, when aggravating internal conditions or external circumstances interact with the root cause condition, or several, erroneous action can be more likely (Sommerville, 2007).

The interactions of root causes have also been investigated by other researchers. The following figure, Figure 2.5, shows Love et al., (2013) conceptual framework of pathogens, errors, and failure. This theory is similar to earlier conceptions that have noted that root causes tend to operate in combination or even in a chain of events that typically leads to the direct cause of adverse events (Busby and Hughes, 2004; Josephson & Hammarlund, 1999; Sommerville, 2007).

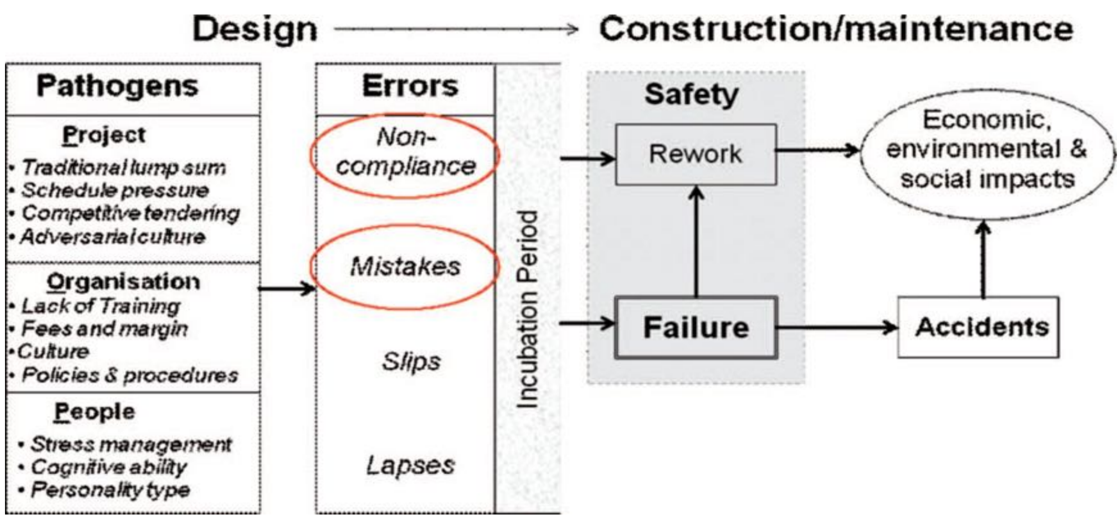


Figure 2.5 Pathogens, errors and failure (Source: Love et al., 2013)

One approach to managing defects is then to focus on basic reasons that lead to undesirable conditions. As point out by Busby and Hughes (2004) the early stages of project delivery can be fertile ground for vulnerabilities, which later lead to defects. Thus, measures should be implemented to prevent and remove potential root causes as early as possible during the construction project's lifecycle so that defects and rework are minimised (Aljassmi, et al., 2013; Huovila et al., 1997; Sommerville, 2007). Despite root causes by definition being latent and often hidden, there are a number of identifying characteristics according to Busby and Hughes (2004) and Sommerville (2007). Root causes tend to be stable. This means that they tend to be conditions that have existed for some time prior to an erroneous action. Moreover, they tend to be overlooked stages of sequences of failure. In other words, prior to the occurrence of an erroneous action, the existence of the root cause is not obvious. However, once the error occurs then the relationship between the root cause and the direct cause is readily identifiable (Aljassmi, et al., 2013).

A number of researchers have investigated root causes in relation to defects in the construction industry. During the years of 1986 and 1990 and later the years of 1994 and 1996, Josephson and Hammarlund (1999) conducted a study into the causes of and costs of defects in the construction industry. The researchers conducted formal interviews with 92 representatives from 7 seven building projects in Sweden, and collected and fully described 2879 defects. The authors preliminary conclusions were that stability in the client organisation, the client's control of the project, the timeliness of feedback, time pressures, the composition of the organisation, cost pressures, top management support, and levels of motivation were relevant root causes (Josephson & Hammarlund, 1999). The authors noted that their findings were not significantly different from earlier studies and advised further deeper analysis be conducted.

Tilley and McFallen (2000) also found that client actions, such as demanding early completion, could also act as root causes to error. The authors found that related cost and time pressures led designers to produce unsatisfactory contractual and design documentation. Similarly, cost and time pressures were noted as underpinning neglect of audits, inspections, reviews and other quality management measures throughout the project delivery. These results have since been found in other studies

(Aljassmi, et al., 2013; Love et al., 2009). Waldron & Association (2006) specifically noted that design documentation was increasingly incomplete at the time of construction due to client led desires to accelerate the construction schedule, and that these are other shortcuts were compromising performance during the construction stage.

Gherardi and Nicolini (2000) investigated error prevention in the construction sector and noted that that failing to view error prevention as a process tended to underpin errors. Failing to embrace quality assurance interventions has been repeated referred to by recent authors (Lopez, Love, Edwards & Davis, 2010; Love et al. 2008). The authors argued that any error prevention system needed to involve a thorough exploration of the organisation, systems, and industry in which it was to be applied. The work, consistent with other quality management interventions, argued that every aspect of the project needed to be taken into consideration, and that the causes and effects of errors were not linear. Tsang and Zahra (2008) conducted a similar investigation and concluded that there was a need to understand how root causes could be "reciprocal or looped in their relationships". (Lopez, Love, Edwards & Davis, 2010).

More recently, Love et al. (2009), through conducting 59 in-depth interviews with participants from construction and engineering firms in Australia, investigated root causes with respect to omission error. The researchers found that pressures imposed by clients relating to increased capital costs, increased expectations and increased competition tended to act as root causes. They also noted that repetitive economic pressures, scheduling, and regulatory matters also tended to act as root causes. Interestingly, the respondents in the study also referred to broader societal issues such as environmental matters and the pressure to accommodate an increasing domestic population as latent conditions, which could contribute to omission error (Love et al., 2009). The authors concluded that the substantial influence of latent conditions lead to a situation where traditional quality control methods targeting variation in the final alone could "never achieve the significant low nonconformance levels" (Love et al., 2009).

Other studies to date have noted that information flows (Aram & Noble, 1999), interdependencies (Williams, 2002), unclear project goals/objectives (Williams, 2002), top-down leadership amongst other things (Love et al., 2010), can impact on the likelihood of erroneous action occurring. It has been noted that scarcity of skilled labour, and corporate liquidity can also underpin the occurrence of errors (Aljassmi, et al., 2013; Hwang, Zhao & Ng, 2013; Love et al. 2010).

2.5.1.1.2 Direct causes

Direct causes are those causes, which can "primarily be attributed to individuals" (Josephson & Hammarlund, 1999). In Love et al. (2013) model presented previously a proposed relationship between pathogens, errors, and failure was provided. Love et al. (2013) listed that pathogens could be project-based, such as those relating to cost and time pressures, organisation-based, such as, lack of training or culture, or people-based such as issues concerning stress management, cognitive ability, and personality type. It is argued that the project-based and organisation-based pathogens can be referred to root causes while people-based pathogens may be more akin to direct causes with respect to construction defects (Love et al., 2013). The dichotomy was also discussed previously in relation to Tah and Carr (2000) investigation of the relationship between risks in construction. As mentioned, the external risks and the global category of the internal risks appeared to better reflect root causes whereas the local risks including labour, plant, sub-contractor, materials, and site tended to have a closer relationship to individuals (Tah & Carr, 2000). As mentioned, arguably these internal local risks provide an indication of source of direct causes of defects in construction, and it is likely that, in most circumstances, the proven reason(s) for the existence of a defect could be isolated from this group.

Busby and Hughes (2004) study of defects in construction provides useful taxonomy of direct causes. Busby and Hughes (2004), through interviews with 22 engineering personnel in a United Kingdom firm, argued the existence of eight categories of pathogens, of which four represent categories of direct causes. Practice was the first category in this taxonomy. This included direct causes that arose from the deliberate practices of people. This was suggested to be the most significant area of direct causes with 62% of errors relating to this category in the study (Busby & Hughes, 2004). This category thus also includes matters of direct supervision and communication. Poor assignment of labour for tasks may also be a direct cause within this category. Chung (1999) found that ambiguous instructions, misinterpretation of drawings, unqualified operators/workers, poor communication with architect(s)/engineer(s), poor sub-contracting coordination, inadequate supervision and neglect of onsite verification were typical causes of defects. Love et al. (2009) noted that this could include a failure to review design documents.

"Task" was a second category. This included direct causes that arose from the nature of the task being completed (Busby & Hughes, 2004; Tserng, Yin & Ngo, 2013). The following figure, Figure 2.6, shows Tserng, et al., (2013) the input flows for a construction task. This could include allocating disproportionate time for tasks (Love et al. 2009). In the original study, 13% of errors related to this category (Busby & Hughes, 2004). However, the authors conceded that due to the fact that determining the precise cognitive process involved in carrying out complex tasks is difficult, it is challenging to identify the specific causes of failure in relation to this category (Aljassmi, et al., 2013; Cheng & Li, 2015). Nonetheless, the authors recommend that breaking down tasks into sub-tasks and their respective requirements would be a difficult but important process for the purposes of reducing task-related direct causes of defects (Love et al. 2009).

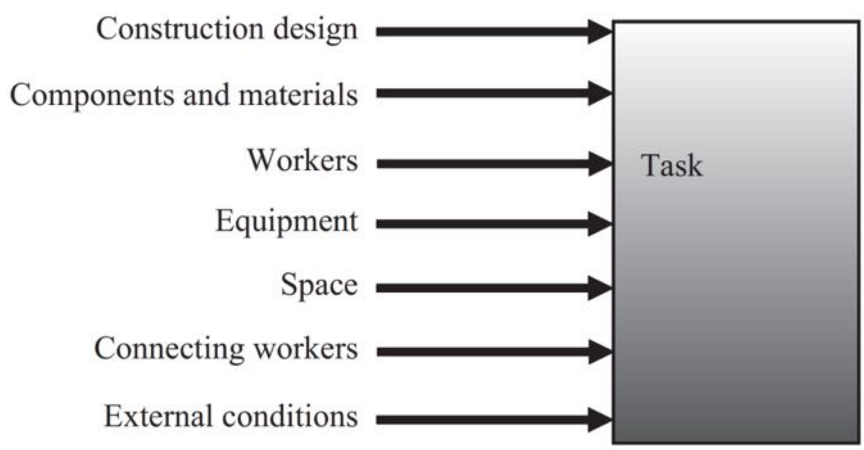


Figure 2.6 Input flows for a construction task (Tserng, et al., 2013)

In addition to this, authors have noted other task-related conditions that would be likely to increase the incidence of error (Busby & Hughes, 2004). Norman (1988) noted that the higher the informational loading, that is, the greater the complexity of each step, the higher the incidence of error. This is because the short-term memory demands could be too high (Love et al. 2009). Similarly when sequential procedural steps are not cued by the preceding procedural steps, or when the succession of tasks is not linear, there can be a greater incidence of error (Reason, 2002). Reason (2002) noted that steps that involve an actionable item that is concealed is likely to be omitted. Busby and Hughes (2004) found that tasks, which require planned departures from customs, habitual actions, or conventions are highly likely to be erroneously completed. Similarly tasks, which involve a repetition of sub-tasks, are likely to suffer error due to a tendency for the repetition to be omitted (Herrman, Weigartner & Searleman, 1992). Premature exits due to preoccupation with the next task, or early completion of the task, by the actor, can lead to steps located near the end of the task sequence to be omitted (Reason, 1998). Moreover, a combination of any of the previously mentioned events can lead to a recurrent error trap (Love et al. 2009).

"Circumstance" was the third category. This category included direct causes related to the situation or environment in which the project was being completed (Busby & Hughes, 2004). In the original study, 6% of errors were due to circumstance. This meant that an extreme weather event, in this sense, would be considered a direct cause and therefore is an example of a direct cause that not primarily attributable to individuals (Love et al. 2009). Another example of a direct cause of an error due to circumstance would be a contractor procuring products in a market where there was insufficient information about the nature and quality of the products (Busby & Hughes, 2004). The "Tool" category referred to direct causes which arose from a technical tool(s). In the original study, 6% of errors were due to convention (Busby & Hughes, 2004). Incompatibility of software would be an example (Love et al. 2009). Technical matters tend not to be a major cause of error in the construction sector according to the authors (Busby & Hughes, 2004).

2.5.1.2 Erroneous actions – Defective works

The term, erroneous action, can be used to refer to any act(s) or omission(s) that constitute a departure from established practices (Josephson & Hammarlund, 1999). There is a close relationship between this concept and the notion of a defect, which as mentioned refers to a deviation from the established requirements that requires rework. Sommerville (2007) argues that erroneous actions generate defects, or alternatively, that the outcome of erroneous actions are defects. Nonetheless, erroneous actions, as defects, are typically underpinned by one or multiple causes (Josephson & Hammarlund, 1999; Love et al., 2013). A substantial amount of past research has been conducted for the purposes of better understanding erroneous actions (Reason, 1998; Josephson & Hammarlund, 1999; Busby & Hughes, 2004). Discussions in the construction literature have included concepts such as miscalculations, misinterpretations (Lopez et al., 2010), omissions, departures (Bea cited in Atkinson, 1998), failures (Hagan & Mays, 1981), deviations (Kaminetzky, 1991), unsafe acts (Reason, 1990) and unexpected occurrences that cannot be entirely attributed to circumstances or chance (Busby, 2001).

There has also been substantial study into the extent that liability for errors can be attributed to humans. Reason (1990) argued that if people accept that making mistakes is a fundamental characteristic of human beings then it is a matter of contention whether individuals can justifiably be blamed for all errors. As part of this, it has even been argued that the concept of errors itself is a social construction. It has been noted "the concept of errors may not exist, as they are a product of a person's cognitive capability" (Reason & Hobbs, 2003, cited in Lopez et al., 2010). It has also been noted that while some argue errors arises due to psychological, physiological, and cognitive limitations, the most severe errors tend to be committed by person's with the highest competencies (Atkinson, 1998; Love, Edwards & Han, 2011; Reason, 2000). It is also argued that error is an innate part of design and other stages of project delivery (Atkinson, 1998; Love et al., 2009).

Notwithstanding this, it is important to outline leading conceptual frameworks in relation to erroneous actions. Arguably The leading view is that poor adaption to cultural, social, and physical environments can lead to impaired human cognitive ability which underpins situational erroneous actions (Henneman & Gawlinski, 2004; Stock et al., 2007; Reason, 2000;). It is argued that erroneous actions can be divided into three categories (Lopez et al., 2010). The first of these are those that arise from an acceptable plan but the actions not being performed as planned. These are referred to as "skill/performance errors". The second category is those that arise from actions being performed as planned but the plan itself being ineffective. These are referred to as “rule/knowledge based errors”. Finally, a third category includes actions which representing overt noncompliance with standards. These are referred to as “violations” (Lopez et al., 2010). The three categories are shown in the following conceptual taxonomy (see Figure 2.7) as adopted by Lopez et al. (2010).

<table>
<tr><td rowspan="10">SKILL / PERFORMANCE BASED ERROR</td><td rowspan="3">LAPSE</td><td colspan="2">Input (or Encoding) Failure</td></tr>
<tr><td colspan="2">Storage Failure</td></tr>
<tr><td colspan="2">Output (or Retrieval) Failure</td></tr>
<tr><td rowspan="7">SLIP</td><td rowspan="4">Execution Slip</td><td>Slip in any goal</td></tr>
<tr><td>Slip in intent</td></tr>
<tr><td>Slip in action specifying</td></tr>
<tr><td>Slip in action executing</td></tr>
<tr><td rowspan="3">Evaluation Slip</td><td>Slip in perception</td></tr>
<tr><td>Slip in interpretation</td></tr>
<tr><td>Slip in action evaluation</td></tr>
<tr><td rowspan="7">RULE / KNOWLEDGE BASED ERROR</td><td rowspan="7">MISTAKE</td><td rowspan="4">Execution Mistake</td><td>Mistake in any goal</td></tr>
<tr><td>Mistake in intent</td></tr>
<tr><td>Mistake in action specifying</td></tr>
<tr><td>Mistake in action executing</td></tr>
<tr><td rowspan="3">Evaluation Mistake</td><td>Mistake in perception</td></tr>
<tr><td>Mistake in interpretation</td></tr>
<tr><td>Mistake in action evaluation</td></tr>
<tr><td>VIOLATION</td><td colspan="3">NON-COMPLIANCE</td></tr>
</table>

Figure. 2.7 Conceptual taxonomy of error (Lopez et al., 2010)

2.5.1.2.1 Errors

As can be noted two-thirds of the previous taxonomy relates to errors. The authors argue that the most encompassing definition of error is that which was provided by Reason and Hobbs (2003) and reads “an outcome that essentially involves a deviation of some kind, whether it is a departure from a path of actions planned toward a desired goal or deviation from the appropriate behaviour at work.” Other definitions are narrower focusing notions of surprise and human liability. For example, Busby and Hughes (2004) argue an error is an act “in which the outcome was appreciably worse than the expectation, could not be put down entirely to chance or circumstances, and involved some element of surprise”. Thus, one of the key recurrent issues appears to be determining the extent that an error can be rightfully attributed particular individuals. As mentioned previously, some argue that error is inevitable despite the skills, knowledge, and/or experience of the proponents (Atkinson, 1998). Recognising this, Hagan and Mays (1981) argued that human error could occur anytime and the precautions were needed, and that understanding the sources of error would support such an effort.

a) Skill-/Performance-Based Errors (Lapses and Slips)

As mentioned, errors that arise from an acceptable plan but the actions not being performed as planned are referred to as "skill/performance errors" (Lopez et al., 2010). This category of errors can also be referred to as "execution deviations" as the error arises due to a departure from the plan (Cheyne et al. 2006), however, importantly they are largely unintentional errors. For this reason, "skill/performance errors" are typically referred to as slips or lapses, and are associated with forgetfulness, memory failures, unconscious routine activity, mental programming (Henneman & Gawlinski 2004), distraction, and preoccupation (Reason, 1995). This is not to say that "skill/performance errors" due to their lack of intent are necessarily minor events. Slips and lapses can lead to significant negligence, carelessness, and recklessness (Henneman & Gawlinski 2004).

Errors that arise from an acceptable plan but the actions not being performed as planned, that is, execution deviations, are said to often occur in patterns regardless of the individuals involved (Love et al., 2009). This may be a result of absentmindedness which results in attentive lapses or slips on a daily basis for many individuals combined with working systems which feature error-provoking conditions (Lopez et al., 2010; Love et al., 2009). Thus, while on one hand, lapses and slips which are characterised as errors where knowledge is correct but failure occurs, and those errors which are typically attributable, to one individual, as Sasou and Reason (1999 cited in Lopez et al., 2010) note "errors in the action process of a single individual and are likely to be divorced from the activities of the team as a whole," on the other hand, there may be a host of contributory factors (Zhang et al., 2004).

b) Rule-/Knowledge-Based Errors (Mistakes)

The second category, as mentioned, are those errors that arise from actions being performed as planned but the plan itself being ineffective. These "errors" are referred to as "rule/knowledge-based errors". Concerning rule-based errors, Reason (1995) notes that this class of errors may occur simply because someone has misapplied a rule. It may have be course of action, that is a rule, that had worked previously but that was not applicable for the current situation, or alternatively it could have been a course of action that did not work and had remain uncorrected. The descriptor "knowledge" is used in the name "rule/knowledge-based errors" to refer to information scarcity and its impact on decision-making. For example, Sunyoto and Minato (2003) comments noting "errors committed of this nature arise from absent or faulty inferences for the correct information that is available." Errors that arise from actions being performed as planned but the plan itself being ineffective are often referred to as "mistakes" (Lopez et al., 2010; Zhang et al. 2004). A justification for this term is that rule/knowledge-based errors are errors that arise unintentionally due to matter being beyond the capabilities of the individual (Kletz, 1985). In other words, the individual may be dealing with a situation in which the he or she possesses incomplete knowledge, and therefore is unable to achieve an effective outcome.

2.5.1.2.2 Intentional Violations/Noncompliances

The third group, as mentioned, is actions, which represent overt noncompliance with standards. These are referred to as "violations" (Lopez et al., 2010). The differentiating aspect of violations is that they are intentional. Van Dyck et al. (2005) refers to violations as "intentional deviations from standards, norms, practices, or recommendations." Similarly, Sunyoto and Minato (2003) in the context of occupational health and safety, define violations as "deliberate ... deviation from those practices deemed necessary to maintain the safe operation of a potentially hazardous system." The intentional nature of violations reflects potentially more serious issues within the organisation. For example, it is noted that violations typically proliferate in environments where there is poor supervision, poor leadership, a perceived lack of concern, and low employee morale (Reason, 2002;

Van-Dyck et al., 2005). In other cases, violations may be underpinned by opportunistic actions of individuals including those which are enacted out of self-interest and those which based on beliefs about improving operational productivity (Love, Edwards, Irani & Walker, 2009).

2.5.1.3 Manifest Defects

The delivery of construction projects involves numerous sub-tasks, which ideally would be carried out adhering to acceptable plans, featuring satisfactory performances, and resulting effective outcomes. In practical terms, an effective outcome would be a product that adheres to established requirements such as the relevant building codes and regulations (Love et al., 2013). However, it is often the case that products do not adhere tightly to these established requirements (Concrete Reinforcing Steel Institute [CRSI], 1996; Fox, Marsh & Cockerham, 2003). Sometimes, the specifications of the final product will differ from the ideal standard in some measures, but still be within an acceptable range (Forcada, Macarulla & Love, 2012). In other words, deviation may exist, but the extent of departure from established requirements is not such as to require rectification actions. The amount of tolerance that is permitted when depend on the relevant regulatory regime as mentioned, as well as client specifications, and practical structural and safety matters (Fox, Marsh & Cockerham, 2003; Jannery 1979). However, once deviations occur that are outside of acceptable tolerances, referred to here on as construction defects, then there can be a much greater risk present and remedial actions will be required. Josephson and Hammarlund (1999) referred to such a type of non-conformity as a "manifest defect" which they defined as "a non-desired condition in the product or process" and "the non-fulfilment of intended usage requirements".

Manifest defects can be categorised broadly. With respect to adhering to the relevant building code, contractors need to ensure that the dimensions and materials are as specified (Love et al., 2013). There are also broader regulations which need to be applied to including laws and by-laws relating to land use, lighting, ventilation, electricity and plumbing facilities, drainage, treatment of materials for corrosion and pest infestation (Ahzahar, Karim, Hassan & Eman, 2011). There may also be additional regulations, which relate to fire protection systems, sound proofing and installation. The improper use of installation materials, for example, may result significant legal liability (Ahzahar, Karim, Hassan & Eman, 2011). Contractors also need to be away of liability that may arise due to defective materials or manufacturing flaws (Ahzahar, Karim, Hassan & Eman, 2011). With respect to client specifications, any deviation from established requirements, which potentially reduces the value of the building, would most likely considered a manifest defect (Ahzahar, Karim, Hassan & Eman, 2011). Concerning structural and safety matters, deviations from established requirements, which could lead to cracks, or collapse will be manifest defects (Love et al., 2013).

As mentioned, human actions and omissions whether in the form of lapses, slips, mistakes, or deliberate violations during delivery of the construction project created systemic deficiency, which can result in, manifest defects (Love et al., 2013). These actions and omissions occur at all stages, however, most notably, it is believed to be during the design and construction stages that origins of most manifest defects can be traced (Tilley 2005). As mentioned, one study in the United Kingdom, found that 50% of errors occurred in the former while 40% occurred in the latter (Building Research Establishment [BRE], 1982). Another more recent study, this time in Russia, found that 30% occurred in the former and 50% occurred in the latter (Volkovas, & Petkevicius, 2011). While the mentioned previous studies reported on the origins of manifest defects for a large number of cases, where the origin of a manifest defect arises with respect to one case, especially when the origin is disputed, the typically procedure is for an independent expert analysis to be undertaken (Comerford and Blockley, 1993). This is typically a cautious and expensive forensic event (Love et al., 2013).

The cost of post-incident investigation is cited as a reason for increased pre-incident quality interventions (Jannery 1979). In one study, it was found that internal design checks could detect 32% of errors, and independent design checks could detect up to 55% of errors present in the design documents (Schneider, 1997). Others have argued that pre-incident quality interventions are most effective when they involve training and skill development to support practices that avoid actions and omissions that ultimately lead to manifest defects (Kvitrand et al. 2001; Love et al., 2013). Nonetheless, despite the origin of manifest defects, their existence in products almost unavoidably results in exposure to cost and time overrun risk, wastage, rework, legal liability including claims on warranties, and adverse implications for client satisfaction and company good will (Fox et al., 2003), as is discussed in the following section.

2.5.1.4 Consequences

The term, consequences, has a negative connotation, and refers to undesirable results, which arise from the existence of a manifest defect. Thus, in this context, "consequence" is therefore broad and refers to, as stated by Josephson and Hammarlund (1999) "all consequences of a manifest defect, which includes consequences for both the product and the process."

As mentioned, the existence of manifest defects in products almost unavoidably results in exposure to cost and time overrun risk, wastage, rework, legal liability including claims on warranties, and adverse implications for client satisfaction and company good will (Cheng & Li, 2015; Forcada et al., 2012; Fox et al., 2003; Love et al., 1999; Mills et al., 2009). Each of these outcomes share a unifying characteristic in that they are very likely to increase the cost of completing the project from the point of view of the principal contractor, and as a consequence, decrease the value of the project to that contractor. The research conducted in different settings to date suggests that the consequences of manifest defects increase the cost of completing projects by between 2 and 20% (Burati et al., 1992; Jafari & Love, 2013; Josephson & Hammarlund, 1999; Love & Li, 2000; Mills et al., 2009). In line, one estimate suggested that contractors spent $1.5 trillion towards completing building projects in the United States in 2004, and that $75 billion of that figure was attributable to rework mandated by defects (Hwang, 2009). Consequences of manifest defects have been found to increase project completion costs more sharply in the residential construction sector compared to the industrial sector (Love & Li, 2000).

Manifest defects by definition require rectification actions, known as rework. These actions where unplanned for can severely impact on scheduling as additional resources will need to be obtained often through hiring arrangements (Davis, 1989;

Love & Edwards, 2004b). Depending on the nature of the defect and rework required there may be substantial interruptions in the roll out of project delivery events. The creation of waste is one of the consequences that impacts on the time required for project completion (Aljassmi, Han & Davis, 2013; Love et al., 2013). Waste, defined as “the loss of any resource, including materials, time (labor and equipment), and capital, that is produced by activities that generate direct or indirect costs but do not add any value to the final product for the client” (Tserng, Yin & Ngo, 2013), once generated can result in out-of-proportion flow-on effects such as delays created by the waste handling process (Tserng, Yin & Ngo, 2013).

Depending on the nature of the manifest defect and the rectification actions required it is probable that the occurrences will adversely affect the relationship between the parties to the project (Love & Edwards, 2004b). The direct consequences of a manifest defect will typically be rework and adversely implications for the cost and timeliness of the project's completion. Indirect consequences arise when parties seek compensation for deviations in budgets and schedules which constitute breaches of contract, and/or when stress, motivation, and/or reputation-related issues result in conflict (Almusharraf & Whyte, 2012; Love & Edwards, 2004b; Palaneeswaran, 2006). While such legal and non-legal disputes will threaten relationships between parties to the project, the occurrence of manifest defects and rework is also likely to suggest to the client that the contractor is unreliable or at least unprofessional and may cause the client to question the overall quality of the work (Eden et al., 2000; Palaneeswaran, 2006). A study in Finland focused on client satisfaction and the “repair of defects and deficiencies noticed during handover inspection,” found that when clients perceive a project to be very poor in one area then they are likely to conclude that the project is poor in all areas (Kärnä, Sorvala & Junnonen, 2009). The authors noted “negative experiences seem to have a great impact on the customer’s entire image of the project” (Kärnä, Sorvala & Junnonen, 2009).

2.5.1.5 Corrective Measures - Rework

Rework refers to the construction-related activities that have to be done more than once due to prior non-conformance (Ashford 1992). It is considered to be a logical last step of defect rectification following root causes, direct causes, erroneous actions, manifest defects, and consequences (Sommerville, 2007). The term is often used interchangeably with rectification actions or corrective measures however, the later is arguably a broader term, as Josephson & Hammarlund (1999) note, encompassing "all actions performed with a view to completely or partly remedying manifest defects, and their consequences". Nonetheless, the different definitions provided for rework contain different themes. For example, rework needed to occur "in the field" according to the Construction Industry Institute [CII] (2001) and expressly included "activities that remove work previously installed as part of the project." Other definitions highlighted the unnecessary aspect of rework. For example, Love (2002) described the concept as "the unnecessary effort of redoing a process or activity that was incorrectly implemented the first time." and, the Construction Industry Development Agency [CIDA] (1995) who define the term as "doing something 'at least' one extra time due to non-conformance to requirements". Other definitions emphasized the potential for rework to be required at any time during the project delivery. For example, it was noted that rework may occur at any stage in any conceived project (Oyewobi, Ibironke, Ganiyu & Ola-Awo, 2011).

The discovery of a need for rework is a critical development in the delivery of a project. The earlier defects are identified, assessed, and treated, the lower the relative expense of such intervention (Eden et al., 2000). Rework will typically be less comparably expensive when it occurs during the planning stages of project delivery such as the preliminary design steps as opposed to rework that occurs during the construction phase (Love & Edwards, 2004b). Similarly, defects that are identified during or after client handover, are likely to involve more complicated rework and expose the contractor to significant financial consequences (Forcada, Macarulla & Love, 2012). The mitigation of risk associated with rework typically takes the form of contract, project, quality and value management interventions (Palaneeswaran, 2006).

2.6 Task Components/Factors and Analysis

A task is defined as "a piece of work that has been given to someone" or alternatively and more broadly "a job for someone to do" (Merriam-Webster, 2012). Another functional definition of a task is that it is an activity that people "should conduct to move their work and life on" (Liu & Li, 2012). In the context of construction, successful project delivery requires that the contractor is able to plan, coordinate, and execute, or have executed, essential tasks (PMI, 2008). Given the increasing importance of goal setting with respect to construction project delivery, it should not be surprising that the concept of a "task" has taken on substantial theoretical significance (Campbell, 1988). Contractors are required to take into consideration the nature of tasks relevant to the project in order to overcome practical barriers which would otherwise led to cost and time overruns and/or poor quality, and ultimately project failure, and use this task reflection to plan a viable plan of execution (Lopez et al., 2010; Love et al., 2009; Priemus and Ale, 2010; Tah & Carr, 2000).

However, task analysis is often absent. Some organisations fail to appropriately break down packages of work into smaller manageable tasks and sub-tasks. Such decomposition is not a difficult process, however, it is reported as time-consuming (Love et al., 2009). In other cases, despite the significance influence of the characteristics of tasks on organisational behaviours, there can be disagreement as to the nature of each task (Liu & Li, 2012; Wood, 1986). Moreover, in the construction sector, research typically focuses on after-the-fact defect and quality issues at the expense of in-depth task analysis (Forcada, Macarulla & Love, 2012; Mills, Love & Williams, 2009; Tah & Carr, 2000). As part of this, the authors note that the sensitivity and susceptibility of tasks are typically under-analyzed (Aljassmi, Han & Davis, 2013; Love et al., 2009). Finally, it is also noted that there is a lack of investigation concerning the nature aspects of tasks. For example, Priemus and Ale (2010) note that misunderstanding of the nature of a task can be a source of construction defect which can occur at any stage of the project's lifespan.

Outside of construction, task analysis has been conducted to some depth. Task-related research appears extensively in the literature of social sciences. The medical industry is one in which is underpinned by considerable research into the pivotal aspects of essential tasks (Bird, 2010; Pittet & Boyce, 2001). Manufacturing is also a sector where task-analysis has been used in depth to streamline processes, remove quality issues, and generate a more successful outcome (Boxall & Macky, 2009). A number of conceptual models have been proposed for better understanding the tasks and in particular likely human performance in relation to tasks. Some of these models focus on structural themes such as the complexity of the task alone whereas other interaction-based approaches focus on the product of the interaction of human agents and the task (Liu & Li, 2012).

A leading approach appears to be considering tasks as comprised by their characteristics (task characteristics), the resources required (task resources), and the environmental conditions (task environment) (Bonner, 1994; Fayek et al., 2003; Liu & Li, 2012; Pitz & Sachs, 1984). The characteristics of a task, also referred to as the nature of a task, encompasses the size of the task, level of dependency, complexity, difficulty, urgency, and information load (Bonner, 1994; Forcada, et. al., 2013; Mitropoulos & Memarian, 2012; Pitz & Sachs, 1984). The resources required refers to the inputs needed and includes personnel, materials, tools, documentation amongst others (Fayek et al., 2003; Liu & Li, 2012). Finally, the environmental conditions of the task, also referred to as the surroundings, or surrounding conditions include matters of climate, wind, noise, site conditions, external interference and even political and social instability (Fayek et al., 2003; Liu & Li, 2012).

The likely strong relationship between task pattern and its susceptibility to quality deviation is the assumption on which this research is based. It is presumed that a more thorough exploration of tasks can lead to accurate characterization of tasks and in particular the respective sensitivities of different tasks to deviation. Moreover, it is expected that close inspection will be able to assist in the identification of sources within sub-tasks that are susceptible to quality deviation. The following section reviews the role of task characteristics, task resources, and task environment, and investigates how these areas interact during action time (task formation).

2.6.1 Identify factors for task elements

2.6.1.1 Task characteristics

As mentioned, task characteristics, also referred to as the nature of a task, are the size, interdependency, complexity, difficulty, urgency, and information load related to the task. Earlier studies in the construction sector tended to focus on the link between construction defects and macro-level issues related to tasks such as whole component quality (Fayek et al., 2003; Macarulla, et al., 2012; Mills et al., 2009). For example, investigations were concerned with deviations in relation to columns, doors, walls, windows, slabs and so on (Forcada, et. al., 2013; Mills et al., 2009). There was a lack of studies focusing on more narrow task or sub-task specifications (Love et al., 2009), and it is believed that the present understanding of task characteristics, particular those characteristics that may have a significant association with quality deviation, is limited (Aljassmi, 2014; Davis, 1989; Love et al., 2009).

Thus, there is a need to better understand the characteristics of tasks. Love et al. (2009) studying causation of error in construction found that 13% of deviation appeared to caused primarily by the nature of the task. Jafari and Love (2013) noted that certain tasks in construction were repetitive and the root of non-conformance could be determined through investigation of such tasks. The size or the scope of a task is a convenient starting point (Priemus and Ale, 2010). This has been defined as "the extent of the area to which the task refers and which is affected by the task outcome" (Whitley & Frost, 1972). Another characteristic of task found in the literature is task interdependence (Aljassmi, 2014; Liu & Li, 2012), which is defined as "the degree to which individuals need to work with other individuals in order to accomplish their tasks" (Tushman, 1978). Task urgency refers to the degree it is necessary to complete the task within a time frame, and task information load, also referred to as task analyzability or task determinacy relates to the extent that information is required to complete the task successfully (Daft & Macintosh, 1981; Liu & Li, 2012).

The task characteristics of task complexity and task difficulty are regarded as critical in their respective effects on task performance. However, they are concepts, which have been interpreted differently. Liu and Li (2012) note "although there are some similarities between these two concepts, they are neither independent or equivalent." The following section inspects these constructs.

2.6.1.1.1 Task Complexity and Difficulty

There are at least five viewpoints on the delineation of task complexity and task difficulty. The first is that the terms are synonymous (Hendy et al., 1997). The second is that task difficulty is a larger concept and that task complexity is a sub-concept (Rouse and Rouse, 1979). This view holds that difficult tasks are not necessarily complex whereas complex tasks are almost always difficult. The third view is that task complexity is the larger concept, which is made up of the components of task structure and task difficulty (Bonner, 1994). Another view is that task complexity is an overarching concept. Altering characteristics may have a greater or lesser impact on task complexity. For example, increasing task size might not alter task complexity whereas increasing the information load will (Campbell, 1988).

Arguably the most convincing and most recent conceptualisation of the terms is that they are different characteristics. Task complexity has been recently linked with the objective cognitive demands of a task whereas task difficulty has been linked to the subjective accessibility of resources to complete the task (Bedny et al., 2012; Liu & Li, 2012). In a study on information searching behaviours, it was stated that task complexity was “an objective property of the search task” and task difficulty was “the context of the individual searcher” (Kim, 2008 cited in Liu & Li, 2012). This objective-subjective dichotomy is consistent with Ajzen (1991) earlier arguments that task difficulty was compatible with perceived self-efficacy. Task difficulty has been linked with subjective temporal perception in other studies (Auli et al., 2010; Silvia, 2003).

2.6.1.2 Task resources

Task resources refer to necessary inputs to complete the task. Human resources, materials, tools/equipment, and documentation are categories (Liu & Li, 2012; Tserng, Yin & Ngo, 2013). Task resources are typically pre-requisites to successful task completion. Numerous studies have investigated relationships between the occurrence of quality deviations and task resources (Pheng & Wee, 2001; Sommerville, 2007).

Human resources appear to the most commonly reported on category, and the category with the broadest items. Love et al. (1997) investigating defect occurrence in construction projects found that trade skills and knowledge, interpersonal skills, communication, experience, coordination, cooperation and collaboration were important resources. Josephson and Hammarlund (1999) study on origins of construction defects in Sweden noted that in addition to knowledge, resources of a psychological or emotional nature including employee commitment, motivation, sense of time pressure, and managerial support were important. The authors also distinguished individual, such as the previously mentioned, and group resources such as effective site organisation. Fayek et al. (2003) study also identified resources relating management such as leadership, supervision, commitment to quality, and clear instruction provision, as salient.

Concerning resources relating to materials, tools and equipment, Tserng, et al. (2013) noted that high quality resources were important. Fayek et al. (2003) studied defect occurrence and noted that compliance with specifications relating to materials, tools and/or equipment, appropriate placement and/or storage of materials, tools and/or equipment materials, and appropriate construction and fabrication of elements were necessary to minimise deviation. Fayek et al. (2003) also noted that reliable and timely supply of materials, tools and equipment was important, and that engineering of materials and review of such engineering was relevant. Documentation resources were found to be essential for successful task completion. Love et al., (2013) noted that specification drawings, information platforms, contracts, and written procedures for internal checks were important resources. Fayek et al. (2003) noted that documentation needed to be accurate and complete.

2.6.1.3 Task environment

Task-condition/surroundings elements are used in literature to describe the surroundings, or surrounding conditions, of the task. This area of consideration may include matters of climate, wind, noise, site conditions, external interference and even political and social instability (Chong & Low, 2006; Fayek et al., 2003; Liu & Li, 2012). As above, these factors may influence task performance, and studies have been conducted investigating relationships between these elements and the occurrence of defects. In Love et al. (1999) and Chong & Low, (2006) studies weather and site conditions were noted as influential on task completion. Josephson and Hammarlund (1999) similarly noted that site organisation could impact on task performance. Fayek et al. (2004) linked elements in the environment that affected task completion to issues of construction, planning and scheduling. The team also noted that surrounding conditions that affected task completion could be characterised as constructability problems. Within this category, the authors listed "safety issues", "access to work location", "unforeseen ground conditions", "adverse weather conditions", "unexpected environmental concerns" and "working environment" (Fayek et al., 2004).

Pheng and Wee (2001) considered the role of surrounding conditions as part of their study on building defect occurrence in Singapore. The authors listed that overlooked site conditions and poor site practices and supervision tended lead to deviation. For the former, the authors noted that "the condition of the soil, the weather, and the amount of space available on the construction site...directly affect the construction methods to be employed as well as the ability to store and prevent material damage prior to use" (Pheng & Wee, 2001). The authors also noted that inadequate soil compaction was an environmental condition that affected the successful completion of tasks on site. With respect to site practices, while these could be attributed to human resource issues, rather than directly to surroundings, the authors noted that "poor material storage" and "handling practices" were issues that could adversely affect the environment in which tasks are carried out, and thereby threaten successful completion of tasks (Pheng & Wee, 2001).

2.6.2 Task analysis

2.6.2.1 General methods for task structure and analysis

Task analysis techniques refer to techniques that are used to describe the goals, operator behaviour, structure, and/or mental processes important to a particular task. Embrey (2000) argues that task analysis techniques should at least provide "a description of the observable aspects of operator behavior at various levels of detail, together with some indications of the structure of the task." Primarily, task analysis techniques have been introduced to reduce risks stemming from particular tasks whether those arise due to human and non-human factors (Kratzer, Gemuenden & Lettl, 2008; Priemus and Ale, 2010). In such cases, task analysis is used proactively aiming to eliminate pathogens or latent conditions that can give rise to erroneous actions and consequences (Busby & Hughes, 2004). Reactive use of task analysis can involve comparing the actual performance of a task with the prescribed performance as part of an incident investigation (Embrey, 2000). Hierarchical task analysis, cognitive task analysis techniques, and decision/action flow diagrams are three commonly applied task analysis techniques.

Hierarchical task analysis is a task analysis technique which focusing on describing the organisation of work in order to meet the organisation's objective in relation to that work (Salmon, Jenkins, Stanton & Walker, 2010). As the name suggests it is a technique that is highly structured requiring that goals, events, operations, and plans for each level are articulated (Kirwan & Ainsworth, 1992; Stanton, 2006). In this sense, hierarchical task analysis typically becomes a representation of the hierarchy of operations within a system (Salmon, et al., 2010). This technique's origins can be traced to Taylorism also known as the scientific management movement, a type of management in which the tasks or processes in a business or activity are divided up into micro-tasks (Boxall & Macky, 2009; Kratzer, et al., 2008; Salmon, et al., 2010). The hierarchical task analysis technique is one, which is flexible. Annett and Duncan (1967), the two authors that much the theory of the technique is attributed to, argue that the depth of description should be justified with respect to the difficult of the task and cost-critical aspects of performance of the task. The authors also recognized inherent weaknesses of the technique noting that generalisation and discrimination tended to exist at higher levels of the structure of tasks. The Annett and Duncan however noted that hierarchical task analysis could be written in an authoritarian manner emphasizing control mechanisms on sub-ordinates, in a delegatory-sub-goal manner emphasizing feedback and sub-functions, or a simply descriptive manner to deal with some of class concepts. More recently, hierarchical task analysis, in addition to its use in error assessment and reduction, is typically applied for human resource purposes such as job design, training program design, team work planning, workload assessment and the design of procedures (Kirwan & Ainsworth 1992; Stanton, 2006).

Cognitive task analysis techniques are concerned with underlying mental processes (Ryder & Redding, 1993). This approach to task analysis is most relevant to the analysis of higher-level mental functions such as those which require professional judgment including diagnosis and complex problem solving (McIlroy & Stanton, 2011). As workplaces are become increasingly automated and reliant on knowledge, it is also more common that employees need to deal with complex situations not anticipated by designers (Salmon, et al., 2010). One characteristic of cognitive task analysis techniques is that they need to assess covert thinking processes. This can be challenging as the evidence of observable actions will need to be interpreted in light of inferences that can be made concerning mental processes. Embrey (2000) argues that effective cognitive task analysis techniques are those, which are able to accurately predict the types of decision errors that are likely to occur in a given setting. Cognitive work analysis is an example of a cognitive task analysis technique. Cognitive work analysis is a task-centered technique, which analyses the constraints and goals that are likely to exist in relation to a task (Salmon, et al., 2010). Cognitive work analysis involves an assessment of the information behaviour in a system and is based on a theory of adaptive control (Fidel and Peijtersen 2004; Hajdukiewicz and Vicente 2004).

Using cognitive work analysis and the strategies analysis diagram to understand variability in road user behaviour at intersections charts are another type of task analysis technique. Decision/action flow diagrams are a type of flow chart, which highlight action and question sequence in relation to complex tasks (Ahlstrom, 2005; Embrey, 2000). As the name suggests, there is a focus on decision making related to the given task. Decision/action flow diagrams tend to be able to developed easily and individual employees typically find them useful for better understanding their own mental pathways (Cornelissen, Salmon, McClure & Stanton, 2013). However, one limitation of this type of flow chart is that the task needs to be relatively simple. This is because complex tasks can lead to decision/action flow diagrams, which are cumbersome and difficult to follow (Embrey, 2000). While the aforementioned three task analysis techniques are common techniques from which there are numerous extensions and adaptations, there is also a wide collection of alternative task analysis techniques available in the broader literature (Ahlstrom, 2005; Cornelissen, Salmon, McClure & Stanton, 2013). While a wider examination of task analysis technique categories is outside of the scope of this review, the following section will deal with task analysis techniques typically applied in construction project management.

Flow charts are another type of task analysis technique. Decision/action flow diagrams are a type of flow chart, which highlight action and question sequence in relation to complex tasks. As the name suggests, there is a focus on decision making related to the given task. Decision/action flow diagrams tend to be able to developed easily and individual employees typically find them useful for better understanding their own mental pathways. However, one limitation of this type of flow chart is that the task needs to be relatively simple. This is because complex tasks can lead to decision/action flow diagrams, which are cumbersome and difficult to follow (Embrey, 2000). While the aforementioned three task analysis techniques are common techniques from which there are numerous extensions and adaptations, there is also a wide collection of alternative task analysis techniques available in the broader literature. While a wider examination of task analysis technique categories is outside of the scope of this review, the following section will deal with task analysis techniques typically applied in construction project management.

2.6.2.2 Task analysis in project management context in construction industry

Task analysis with respect to the management of construction projects typically begins with the "identification of project scope" according to the Project Management Book of Knowledge (2008). This is the first step of project management and requires an identification and analysis of the project's assumptions, constraints and deliverables and the tasks required to achieve them. Formally, the "identification of project scope" will require the drafting of a "project scope statement" which includes product scope description, product acceptance criteria, project deliverables, project exclusions, project constraints, and the project assumptions (PMI, 2008). The "product acceptance criteria" outline the processes and criteria for accepting the completed products based on the applied standards. The drafting of the "product acceptance criteria" is an important task analysis activity formally providing the project team with details about the work to be performed and how well can it be controlled (PMI, 2008).

The “project deliverables” section of the “project scope statement” describes the required project outputs in detail. A work breakdown structure (‘WBS’), a deliverable-oriented hierarchical decomposition of the work, is used as part of this process to subdivide project deliverables into smaller manageable components called “work packages” (PMI, 2008). Each work package is decomposed into a number of necessary activities to achieve the work package. Activities are defined as “the process of identifying the specific actions to be performed to produce the project deliverables” (PMI, 2008), and must include required resources (such as people, material, and equipment) for each activity, the expected duration, activities sequence based on priority, and the appropriate schedule. Furthermore, each activity is described in sufficient details to ensure that the work members understand all the requirements for successful completion of the activity (PMI, 2008). The depth of work package details differ depending on the project’s size. However, as far as the WBS approach is concerned, the work-package level is the lowest level from which time can be scheduled, costs can be estimated, and work can be controlled.

2.7 Previous Studies on Modeling the Defects Prediction

The relationship between defect occurrence in the construction industry and adverse consequences such as cost and time overruns and stakeholder disputes is well-documented (Cheng & Li, 2015). However, defects rarely arise as an outcome of an isolated cause. In fact it is the combination of interrelated direct causes where much of the attribution of defects lies. This combination is referred to as a defect pathway. As there are numerous pathways from which defects can occur, analysts have argued that the frequency, that is the number of risks, that is the severity of the risk to the pathway formation, can be determined (Aljassmi & Han, 2013). To date, the focus of inquiry has typically been the identification of generic defect causes. However, it has been argued that an in-depth analysis of the comparable frequency of risk of defect causes is lacking (Aljassmi & Han, 2013). Moreover, it is also argued that an adequate analytical model is lacking to make sense of information from the database of generic construction defect causes (Cheng & Li, 2015). Thus, to date, the challenge of developing association rules for effective causation analysis and defects prediction appears to remain.

Dissatisfied with the fundamental flaws and practical difficulties of multivariate regression techniques to measure quality concepts, concepts which are not easily quantified, Molenaar et al. (2000) investigated the use of an extension to standardised regression modelling developed to deal effectively with independent variables which are typically poorly measured. The technique was referred to as structural equation modelling (SEM) analysis. Based on qualitative and quantitative surveys of 159 construction projects, the team was able to investigate a number of quality issues and their suspected causes. The authors concluded that in comparison to the original logistic regression modeling methodology, the SEM analysis was able to provide information with respect to the interaction between suspected causes, and was able to better deal with errors in measurement. The qualitative component of the model was reported to assist in explanations of correlations. The authors noted "There was unanticipated correlation among variables that were necessary to produce a well-fitting model" (Molenaar et al., 2000).

Kim et al., (2009) also dissatisfied with the lack of accuracy and coordination of early models, investigated the use of SEM analysis in the context of construction. The team attempted to predict the success of construction projects operating in uncertain international settings. The team compared multiple regression analysis, artificial neural network, and SEM analysis and reported that the latter was best equipped to analyse and represent causation variables in a realistic manner. The team also noted that SEM analysis aided effective visual representations of risk pathways enabling proponents to achieve "critical" early understanding of project conditions (Kim et al., 2009).

Another approach to model analysis, which has been applied to the construction sector, is system dynamics (SD) modelling. This approach focuses on the non-linear behaviour of complex systems. This area of study focuses on the longitudinal structure of relationships using feedback loops and time delays, as opposed to predicting a specific output such as an erroneous action leading to a defect. This means that the strength of SD modelling lies in demonstrating sequence non-linearity. Chapman (1998) reported on his use of SD modelling to demonstrate the effects of the loss of key personnel and issues, which aggravated assimilation of new recruits in construction. Chapman concluded that the technique "offered a way of modelling the design process which reflects the underlying pressures and the critical issues which erode productivity" (Chapman, 1998). In the context of defect prediction and causation analysis, the use of SD modelling could enhance understanding of interdependencies between latent conditions and direct causes of deviation.

Love et al. (2002) applied SD modelling in relation to changes that affect project management and specifically the incidence of rework. The team identified decision-making, techniques and technology, behavioural responses, project structure as four dynamics that were typically attended to by construction project management teams. Similarly, five internal unattended dynamics were identified and eight external unattended dynamics. The team concluded that the approach was helpful in identifying the impact of unattended dynamics, so that actions can be implemented to increase dynamics that positively affect operations and decrease those that negatively do so. With respect to SD modelling, the team noted that it was a useful approach to investigate "whether the project objectives are compatible with overall company objectives" and "strategic alternatives of an individual project" (Love et al., 2002).

Han, Lee, and Pena-Mora (2012) investigated the use of a SD modelling analysis approach for the identification and assessment of non-value-adding effort in the context of the construction of a bridge. The team trace previous research in the sector distinguishing microlevel analysis, that is, an analysis of the unnecessary steps within an action, such as waiting, or moving, causing non-value, and macrolevel analysis, that being an analysis of external factors, such as change orders or site conditions. Combining a qualitative feedback mechanism model and a quantitative computerised simulation model, the authors reported that the SD modelling approach was successful in capturing the propagation of non-value-adding effort between interdependent activities. Moreover, the authors reported that the modelling approach could be used to assist managers in planning construction. Project management could theoretically reduce non-value-adding effort by "inserting an appropriate time lag or assigning a smaller number of resources where a significant amount of interruption is expected" (Han et al., 2012).

Li and Taylor (2014) also investigated the use of SD modelling to identify points of high leverage with respect to the mitigation of rework and its consequences. The authors noting “available knowledge is not always successful in improving project managers’ understanding of the feedback mechanisms,” (2014) reviewed interactions across different phases on project delivery. By applying SD modelling, the authors were able to describe the likely effect of undiscovered rework as it combines with other variables, referred to as “ripple effects” on overall productivity. The authors further reported discoveries in relation to potential solutions based on feedback from the SD model. The authors reported that the model aided in the development of an empirical explanation of the relationship between rework discovery timing and rework consequence magnification (Li & Taylor, 2014).

Palaneeswaran et al. (2008) investigated the use of an artificial neural network (ANN) -based technique to predict defects. ANNs are typically a family of statistical learning algorithms that are used to estimate or predict functions or events. ANNs operate by following specific learning rules and ultimately learning the behaviour, which underlies a given system. ANNs are trained on a set of known patterns and are then tested on a distinct test set. The team focused on identifying defect root causes, which had some likelihood of occurring during the construction phase. The team used back propagation neural network (BPNN) and general propagation neural network (GRNN) architectures, and data from 112 construction projects in Hong Kong in an attempt to identify relationships between causes of errors and consequences of errors in construction. While the team identified practical limitations with their study including data set shortcomings, non-optimal explorations of modelling, and problems with impracticability of measurements, the team was able to conclude that ANN modelling would most likely lead to development of effective performance prediction models in construction and that particular critical decision-support resources could be developed.

Path analysis is a sub-set of SEM, and only deals with measured variables. Path analysis can be distinguished from other linear equation models due to its ability to understand the comparative strengths of direct relationships as well as indirect relationships with respect to a variable set. As Love et al. (2009) note “In path analysis, mediated pathways (those acting through a mediating variable, i.e. ‘Y’, in the pathway X → Y → Z) can be examined" Love et al. (2009) used this technique with data from 147 completed buildings and 113 completed civil engineering projects to identify and assess path coefficients that predicted rework. A structural model was developed and it was found that "client-directed changes, site management and subcontractors, and project communication" were the pathways that were most statistically significant in terms of contribution to rework costs. One interesting result of the pathway analysis was that there was no significant difference between direct and indirect cost of rework incurred by the civil engineering projects and that of the construction projects. Similarly the analysis revealed that factors causing rework were also not significantly different between the civil engineering projects and the building construction projects. The researchers concluded that path analysis was a useful technique to inform matters of causation, however there was also a need to focus to investigation best practice mitigation of rework.

Despite the aforementioned attempts to model quality issues in construction, Aljassmi and Han (2013) argued the need for a sophisticated quantification of independent variables, namely latent conditions and direct causes with respect to their effect on dependent variables, namely, erroneous actions and defects. Applying a fault-tree approach and data from four residential projects the authors investigated latent conditions and causes of defect in terms of their risk importance, namely their frequency and magnitude. The fault-tree approach involves the quantitative analysis of instances of erroneous actions and defects and studying the combinations of contributing latent conditions and/or causes. The technique also uses practitioner observations about specific defect causes as an input. Probabilistic parameters are constructed and a fault tree is developed. Important from a practical point of view the fault tree includes the use of measures of risk importance. Thus, latent conditions are characterised in terms of frequency and magnitude. While high frequency latent conditions can theoretically contribute to a high number of defect pathways, it is the latent conditions with high magnitudes, which poses the most immediate threat due to high sensitivity of the defect occurrence in relation to the presence of the high magnitude latent condition.

Aljassmi, Han and Davis (2014) extended on the fault-tree approach of Aljassmi and Han (2012), and used a social network analysis (SNA) approach to identity and evaluate defect cause interrelationships. Moreover, the team developed SNA metrics so that the “pathogenicity” of each latent condition could be mathematically expressed. The authors referred to the novel approach as a project pathogens network (PPN) methodology. The team reported that the PPN approach was able to provide a mathematical and visual representation of the “pathogenic capabilities” of latent conditions in terms of the their propensity to cause defects. Nonetheless, the researchers reported that limitations of the approach were that its effectiveness depending on the ability of interviewers to guide interviews and that the data collection process was time-consuming.

Another approach used to identify the frequency and magnitude of latent condition and/or causes and defect occurrence was carried out by Forcada et al. (2013) who used a contingency and correlation analysis with respect to 2351 post-handover defects from a four builders and seven residential development projects. The statistical approach aimed to identify and test associations between defects and their sources, namely, design, lack of protection, workmanship, and materials, and defects and their origins, namely, change, damage, error, or omission. With respect to the source of defect cause it was found that bad workmanship, namely the execution or construction stage was most relevant while in terms of origin of defect errors and omissions were found to be the most relevant. While studies based on statistical approaches have been found to provide reliable and valid information with respect to defects, they have been criticized for neglecting relationships between multiple defect variables (Cheng & Li, 2015).

One of the most recent approaches to causation analysis and defect prediction was reported by Cheng & Li, (2015) who investigated the application of a Genetic Algorithm (GA)-based approach incorporating construction defect concept hierarchy for the purposes of identifying multi-level patterns of defects. The team applied to GA-based approach to data concerning defects in a ten-year period (2000 to 2010) in China. The team incorporated domain knowledge relevant to a defect into a concept hierarchy. This enabled an adjustment of the data retrieval depending on the concentration of data and relevance of a rule. The team reported that the GA-based approach was able to generate association rules without minimum confidence thresholds enabling a more flexible search capability. Cheng & Li, (2015) reported that the technique was particularly useful for discovering previous hidden knowledge in the form of significant relationships between causes and defects in historical projects.

There is a need for a more organised and systematic approach to causation analysis and defect prediction. A vital addition to the current body of knowledge would appear to be the development of a database compilation of historical cases of defects. The development of this resource would enable preprocessing and reuse of information. This approach has already been applied in different contexts such as safety management, chemical accident analysis, and accident investigations. As part of this, there is a need to develop domain ontology that is specific to defects and a data collection system that permits the effective use of information concerning defects and defect factor patterns (Cheng & Li, 2015). Preliminary work has commenced in these areas with Park et al. (2013) proposing a domain ontology to search and retrieve defect information from historical projects. Similarly, Lee et al. (2013) have developed a relational database to store quality and defect related data.

2.8 Chapter Summary

The chapter provided background to the research and commentary relevant to the broader topic of the construction industry and the more narrow topics of deviation and defect causation. The chapter provided a topic-by-topic review of quality management in the construction sector providing definitions to key concepts such as quality deviation and construction defect. The chapter also reviewed the prevailing theoretical frameworks that have been presented to help understand quality issues in the construction process. A significant portion of the chapter was dedicated to reviewing the notion of the task within construction. Definitions were provided and an analysis of task characteristics such as task resources and task environment was also presented. The chapter provided a review of modeling approach(es) that have been used within the field of deviation (from quality norms) in construction to date.

CHAPTER 3: Research Methodology

3.1 Introduction

The purpose of this chapter is to present the theoretical framework and methodology of the research and to tie these concepts to the objectives of this study. The chapter attempts to achieve this through outlining the conceptual framework and the research aim. The philosophical assumptions and claim to knowledge of the research are presented. The chapter presents the rationale for and application of a mutliple-case study approach. The unit of analysis selected, namely, the sub-task requirements STR, is described at length. The chapter also elaborates on the justification for the selection of a multiple-case approach involving 17 cases (across 27 construction sites). The chapter describes the development of the data collection instrument including the role of documentation, structured interviews, observation, and direct measurement processes. The processes for attesting the instrument's content validity are also outlined. The rationale for, and application of, data analysis techniques applied in the study are discussed in the chapter. Finally, the chapter outlines the tests of data validity and reliability that were conducted and provides a summary and the main conclusions.

3.2 Research Conceptual Framework

The review of the literature outlined the background to quality deviation and defect occurrence in the construction industry. Most studies refer to the existence of complex pathways of events from root causes, to direct causes, erroneous actions, and defect occurrence. In the relation to the direct causes, the majority of these studies have identified and evaluated the role of non-task factors, such as worker, supervision, resources, documentation and surroundings conditions with respect to quality deviation or/and defect occurrence.

To date, there are have been relatively few empirical investigations focused on the role of task-related factors (i.e., task requirements), such as, sensitivity towards deviation (see Figure 3.1). Moreover, while isolated research and commentary focuses on the task-related factors, these reports tend to view the task from a superficial level. In other words, there appear to be very few empirical publications concerned with the specific requirements of sub-tasks and how performance of these sub-tasks can provide information useful for understanding deviation and defect occurrence. While STRs are available in building codes there appears to be failure from the research community in terms of using these standards to better understand how discrete aspects of tasks can affect the likelihood of defect occurrence. In other words, while it appears building code STRs provide a useful benchmark from which performance can be evaluated, and the sensitivity of different sub-tasks to deviation can be ascertained, such an approach appears not to have been investigated thus far.

To address this gap in the research, the sensitivity of each of the STRs towards quality deviation will be quantified. Then the direct causes leading to deviation for each STRs, as shown in Figure 3.1, will be investigated in order to understand the most influential causes of deviation for each respective STR. These measurements will be achieved through the development of a model capable of simulating actual interaction between each STRs and the relevant direct causes leading to deviation.

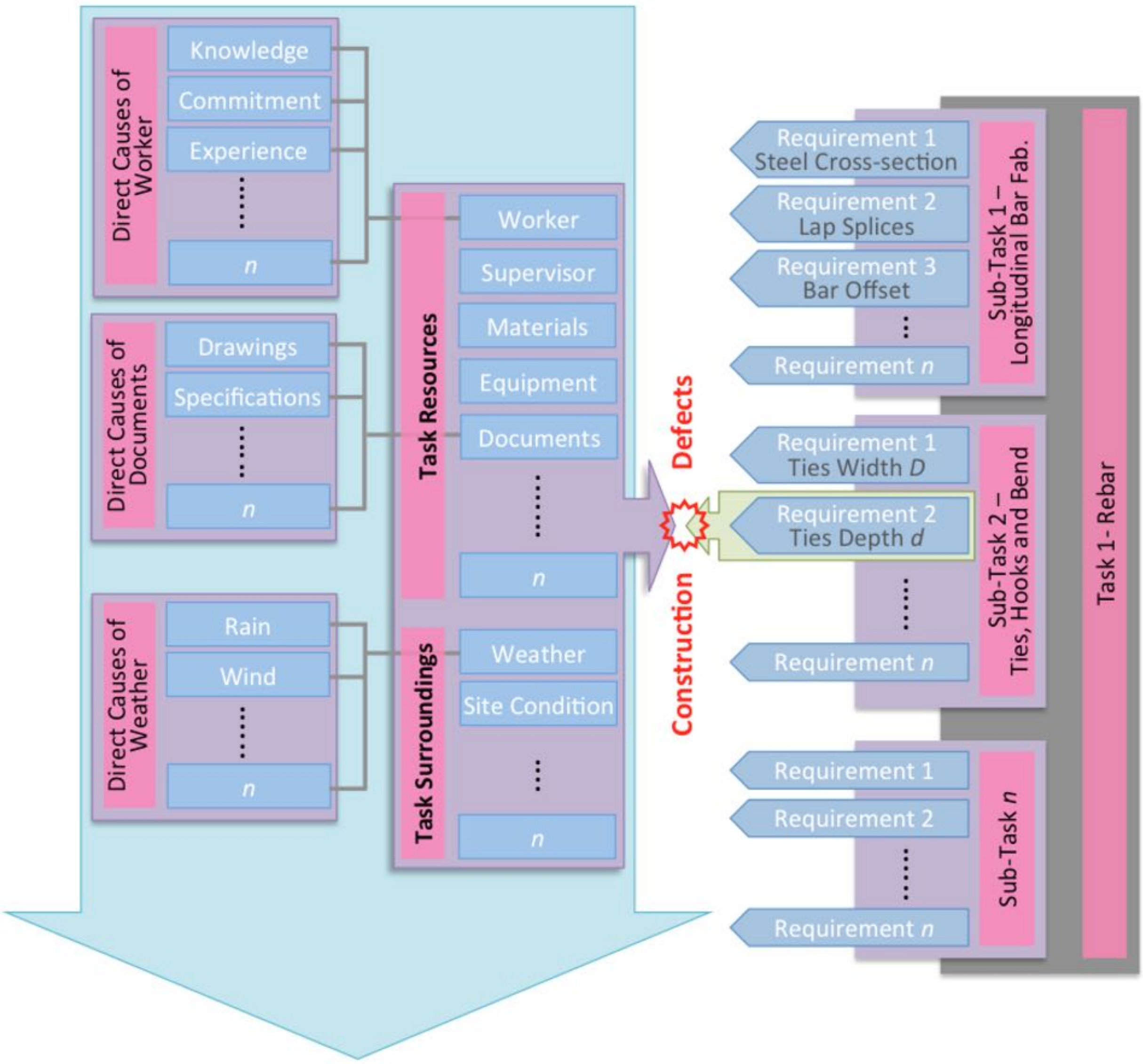


Figure 3.1 Research Framework

3.3 Research Aim and Objectives

3.3.1 Study's Aim

The main objective of this study is to develop an approach to determine patterns of the quality deviations and defect occurrence in the construction industry using a novel quality deviation classification system and novel model to simulate interaction between deviations of STR and direct causes (see Figure 3.1), these being task resource and task surroundings conditions. Six objectives (restated below) are proposed to achieve the main aim of this study as the following:

3.3.2 Objectives

1. Identify the factors relevant to quality deviation and defect occurrence in the construction industry from literature review (Chapter 2).
2. Measure the susceptibility of individual STRs to quality deviations to determine if isolated STRs exhibit different deviation patterns (Chapter 5). To address this objective, the researcher will identify design specifications for specific sub-tasks from requirements from building codes (e.g. SBC and ACI) and project documentation (e.g. drawings, specifications, bill of quantity, etc.), and use these parameters to set targeted measurements and range of tolerance and maximum/minimum boundaries for each specific sub-task. These points will be used to measure deviation degree.
3. Classify each STR into one of six novel classes as a means to better understand patterns of deviation occurrence (Chapter 6). To address this objective, an anatomical analysis for each isolated STR will be conducted to present performance for each STR. The frequency of occurrence for each of the six classes will be determined and used to assist better understand patterns of deviation occurrence. Also, identify deviation source as either design phase or execution phase through classifying the degree of sub-task deviation against design specifications and building code requirements.
4. Measure and rank the sensitivity towards each class from one STR across all STRs. This is to determine accurately the level of the variation and sensitivity between the STRs (Chapter 6).
5. To develop and test a novel BBN-based model capable of simulating realistic interaction of quality deviation with its causes at the STR level (Chapter 7 and 8).
6. Provide recommendations with respect to the nature of STRs in concrete structural construction and model quality deviation and defects (Chapter 8 and 9).

3.4 Philosophical Assumptions and Research Strategy

Research must be underpinned by a satisfactory examination of relevant philosophical matters. This is done in order to ensure that the research objectives are addressed using the most appropriate data collection and analysis techniques given the context (Easterby-Smith et al., 2002). More specifically, review of competing philosophical positions is a helpful technique to detect limitations of the anticipated research, and allow for such to be minimised through modifications of inquiry methods.

3.4.1 Claim of knowledge

The claim of knowledge of a research project is the starting point of any satisfactory philosophical examination (Lincoln & Guba, 2000). The purpose of articulating a claim of knowledge is to help ensure that the researcher has investigating philosophical matters such as "how they will learn" and "what they will learn" during the research project (Creswell, 2009). An investigation's claims of knowledge is also referred to as its paradigm (Lincoln & Guba, 2000; Mertens, 1998), its philosophical assumptions (Crotty, 1998), its ontology or epistemology (Crotty, 1998), or as its methodology (Neuman, 2003). A thorough claim of knowledge will include the researcher's beliefs about what there is in the world (ontology), researcher's beliefs about how one can know knowledge, (epistemology), as well as the values which shape knowledge (axiology), the language that can be used to convey knowledge (rhetoric), and processes that can be used to investigate knowledge (methodology) (Creswell, 2009).

It is most convenient to summarise the history of positivism as an introduction to the evolution of schools of thought on examinations of relevant philosophical matters. It was the work of Francis Bacon and Augusto Comte rejecting that knowledge could be gained from theology, metaphysical speculation and deduction that led to the development of positivism. These philosophers argued that in order for knowledge to be gained it must be observed and tested (Collen, 1992). Positivism is the scientific tradition that sees science itself as a "organised method for combining logic with precise empirical observations of individual behaviour, in order to discover and confirm a set of probabilistic causal laws that can be used to predict general patterns of human activity” (Neuman, 2003). Positivism has since become known as the approach of the natural scientist (Neuman, 2003). In many ways, positivism, was the first of the scientific traditions, being a method based on rational and empirical philosophy (Mertens, 1998). Positivism is also deterministic in the sense that the paradigm assumes that one reality is possible (Creswell, 2003). This belief of universal truths is further underpinned by an assumption that the data collection and analysis processes are independent and objective. This presumption of objectivity leads researchers adhering to this paradigm to adopt measures, which are believed to be exact and rigorous (Neuman, 2003). The problem with positivistic approaches to research is that they tend to oversimplify complex systems. In other words, while providing rigorous assessment of a particular dependent and independent variable, potential confounding conditions can be neglected. These extraneous variables may include critical practical and ethical issues relevant to the subject matter (Collen, 1992). The notion of the “absolute truth” was attacked on these grounds by a number of philosophers including Karl Marx.

The response to these criticisms was the evolution of the post-positivism paradigm (Lincoln & Guba, 2000). Primarily this paradigm argued that while the real world exists, it needs to be discovered by researchers and is it open to different interpretations (Gray, 2009). The primary distinction between positivism and post-positivism is the while the former holds out that a sole source of knowledge is achieveable, the latter argues that perceptions of researchers are not reality, and instead are merely perspectives of specific reality. The post-positivism approach while maintaining many of the principles of positivism further adds that triangulation and consideration of source of bias are required to achieve a more accurate depiction of reality (Godfrey & Hill, 1995).

While positivism and post-positivism together constitute one of the two major scientific traditions, on the other side, are claims of knowledge based on constructivism. This second scientific tradition holds that participants are able to construct their own understandings and meanings for phenomena. The construction of these understandings is moderated by that individual's exposure to social and/or historic events. Three claims of knowledge derived from the constructivism tradition warrant description. The first is socially constructed knowledge claims. This an approach based on inductive reasoning in which the researcher focuses on the expression of the participants' lived experience. Crotty (1998) identified that the interaction of a person with his or her external world is influenced by that persons' social and historical perspective. Humans are socially programmed by their own unique cultures. Another perhaps more radical claim of knowledge based on the constructivism tradition are participatory knowledge claims. These claims of knowledge arose in response to a perception that positivist and post-positivist assumptions led to a situation whereby disadvantaged and marginalised persons in society more systematic neglected. Most researchers within this field draw inspiration from Marx (Creswell, 2009). These approaches have also been referred to as emancipatory approaches and share similarities with post-modern philosophies. The pragmatic claim of knowledge is the third paradigm based on constructivism and tends to advocate a "free" approach to methodology rejecting the post-positivism importance of antecedent conditions and causation.

Due to the focus on observation and measurement, this study adopts a post-positivism claim of knowledge.

3.4.2 Strategies of inquiry

The strategy of inquiry of a research project refers to a more applied level of considerations that relate to the specific direction of the research. Strategies of inquiry are also referred to as "traditions of inquiry" (Creswell, 1998) or "methodologies" (Mertens, 1998). Strategies of inquiry, as claims of knowledge have diversified over time. Notwithstanding this, the dominant strategies are the quantitative strategy, in which the researcher deals with data in the form of numbers and statistics and uses to equipment to collect such data, and the qualitative strategy, in which the researcher deals with data in the form of words, and uses instruments to gather such data. A third strategy of inquiry which requires mention is the mixed-methods approach in which quantitative and qualitative data sources are used in order to neutralise the inherent limitations of each approach (Creswell, 2009).

The strategy of inquiry for this research project is the quantitative strategy. This strategy is reported to be appropriate within the post-positivist perspective of knowledge. Quantitative strategies are typically applied in the context of experimental studies, and quasi-experimental studies. However, the quantitative strategy is also increasingly applied in non-experimental designs, those investigations without treatment or random assignment, including surveys, questionnaires, structured interviews, and other assessment based on careful observation and numeric measures (Creswell & Clark, 2007). It is also possible for a number of these non-experimental quantitative data collection and analysis techniques to be conducted and presented in the form of a case study. While the case study approach is commonly aligned with qualitative strategies, Yin (2009) notes that "case studies can include, and even be limited to, quantitative evidence." Yin argues in this regard that "any contrast between quantitative and qualitative evidence does not distinguish the various research methods (2009)." Yin further noted that the case studies are appropriate in situations where the situation is technically distinctive and multiple sources of evidence are available. Moreover, the case study approach, including a quantitative case study is appropriate where "the prior development of theoretical propositions" can be used to guide data collection and analysis (Yin, 2009).

3.4.3 Research methods

Having adopted a post-positivist claim of knowledge and a quantitative strategy of inquiry, the next area for consideration is the nature of the specific research methods to be applied. Creswell & Clark (2007) advises that researchers adopting such as claim and strategy pattern need to develop data collection techniques, which have their parameters, pre-determined and which collect numeric data. Where data are collected from surveys, interviews or observations of human participants schedules should use close-ended questions and/or use numeric ranking systems.

The claim and strategy chosen also infer a responsibility on the researcher to adopt approaches to data collection, which are as free as possible from bias. The use of technical equipment for objective measurement may be appropriate in this context. In order to increase the reliability and validity of the results of the study, investigators adopting a post-positivist quantitative approach are typically required to employ statistical procedures (Creswell & Clark, 2007).

3.5 Research Design

The research design is often thought of as the blueprint of the study and refers to the planning and organisation of data collection and analysis techniques (Poilt and Hungler, 1985). The research design as a "blueprint" is a key strategic document aimed at assisting the researcher in meeting his or her objectives (Mohamed, 2004). The research design will provide detailed information about the size, nature, selection, and recruitment of the sample used, as well as the methods that will be applied to collect/gather data, and how specific variables and concepts will be measured and interpreted (Cavana et al., 2001).

Creswell & Clark (2007) advises that each research design should be selected based on a consideration of best match between the problem and the strategy (as shown in Table 3.1). In other words, the approach should be appropriate and proportionate to the topic. Creswell & Clark (2007) also advises that the researcher's personal experiences and the addressees or intended audiences of the research should be taken into consideration. To improve appropriate research design selection, Creswell & Clark (2007) provides the following table. The non-experimental yet quantitative nature of the proposed research suggests that the first three items, "Identifying factors that influence of an outcome", "Understanding the best predictors of outcomes", and "the utility of an intervention" are most relevant and have therefore been selected (as shown in Table 3.1).

Table 3.1 Match between problem and approach

	Criteria for Selecting an Approach
Quantitative approach	• **Identifying factors that influence of an outcome** • **The utility of an intervention** • **Understanding the best predictors of outcomes** • Testing theory or explanation
Qualitative approach	• Understanding concept or phenomenon • Understanding on little research done on its • Understanding on problem that important factor is unknown (being new topic) • Understanding the particular sample or studied group that existing theories do not apply for • In natural setting
Mixed Methods approach	• Wanting of both generalization and detailed view of the meaning of phenomenon or concept for individuals

The researcher's personal experiences and the addressees expectations have also been taken into consideration. With respect to the former, the principal researcher and supervisor have extensive experience using quality management tools and techniques and statistical analysis, and this experience has been drawn upon towards ensuring the most appropriate techniques. With respect to the former, conducting a thorough literature review has helped ensure that the research is planned, conducted and presented in accordance to prevailing academic and industry conventions as far as practicable.

Thus, as mentioned, a positivist/post-positivist claim of knowledge and a quantitative strategy of inquiry have been adopted for this study. To address the objectives of the study, it has been determined that a number of data collection and analysis techniques will be applied including but not limited to direct measurements, checklist observation, document analysis (i.e., drawings, specifications, and bill of quantities) and structured interviewing. To encompass these techniques in a coherent manner a quantitative multiple-case studies methodology was applied. An overview of the research design is provided in the following table, Table 3.2.

Table 3.2 Overview of research design

Research Objectives	Claim of Knowledge	Strategy of inquiry	Research Method	Analysis Method
Identify the quality deviations causes	N/A	N/A	Literature Review + Interview	N/A
Measure susceptibility of the quality deviations of STRs	Postpositivism – *Empirical observation and measurement*	Quantitative Research – *Multiple-Case Studies*	Field study– *Direct Measurements for 17 STRs*	Statistical Analysis - CPI
Measure the sensitivity of the quality deviations of STRs			Field study– *Self-observation for 17 STRs*	Statistical Analysis - Chi-square χ^2
Rank the sensitivity of the quality deviations of STRs			Field study– *Document analysis: gathering design information*	Statistical Analysis - Odd Ratio OR
Modeling the quality deviations causes			Field Interview – *Structure interview with supervisors and workers*	Statistical Analysis – BBN
Validation and reliability	N/A	N/A	Interview + Statistics Analysis	Spearman's rho ρ & MMRE

As mentioned, it is possible for multiple-case studies to be based entirely on quantitative data (Bryman, 1989; Yin, 2003). The central defining features of case studies are that they involve the evaluation of multiple sources of evidence and that they investigate a phenomenon in its real-life context (Yin, 2003). Matters of production control in the construction sector and often researched applying a case study methodology due the contextual complexities of the subject matter.

Here, while a quantitative case study methodology is applied, the unit of analysis is the amount of deviation compared to permissible tolerance per sub-task requirement. In all, 17 sub task requirements were investigated and therefore it could be said that the research design, was a multiple-case design, or more specifically, an analysis of 17 case studies.

A research approach can be considered as consisting of seven phases. The first phase involved the identification of the research topic, the development of a research plan, and the submission of a formal proposal. The second phase involved an in-depth review of the literature with respect to quality practices in construction industry, deviation and defects, the nature of tasks relating to construction, approaches to task analysis, and the relevant modeling of such phenomena. Thirdly, the research instruments' purpose and form was developed. This included the precise direct measurements that would be conducted, observation checklists and schedules, document analysis techniques (i.e., drawings, specifications, and bill of quantities) and interview structure for project supervisors (project or quality manager) and labor. Once these instruments and processes were determined, the research moved into the fourth phase namely the data collection processes. The fifth phase concerned the data analysis activities. This involved capability process index CPI, chi-square χ^2, odd ration OR, and Bayesian belief network BBN. Statistical packages, such as Matlab, SPSS, and BaysiaLab, were used to perform the required analysis. The sixth phase involved consideration, discussion, and reflection on the results of the study particularly with respect to quality deviation and defects issues and modeling the interaction between the nature of tasks, task-resources and the workplace condition. Finally, in the final phase, the conclusion and recommendations of the study were considered. The objectives, data collection techniques, data analysis techniques, and relevant pathways are shown in the following figure, Figure 3.2.

3.6 Literature Review

As can be seen the literature review assumes an important preliminary position with respect to this research project. In addition to identifying and evaluating the research problem more generally, the purpose of the literature here was to provide a solid background concerning prevailing quality practices and challenges faced by the construction industry in particular quality deviations and defects, building-project task analysis and task analysis more broadly, and current leading approaches to modeling quality deviations and defects in the building sector. Part of the literature review here was also dedicated to the operation of statistical analysis techniques in order to better understand subsequent data preprocessing and steps of analysis.

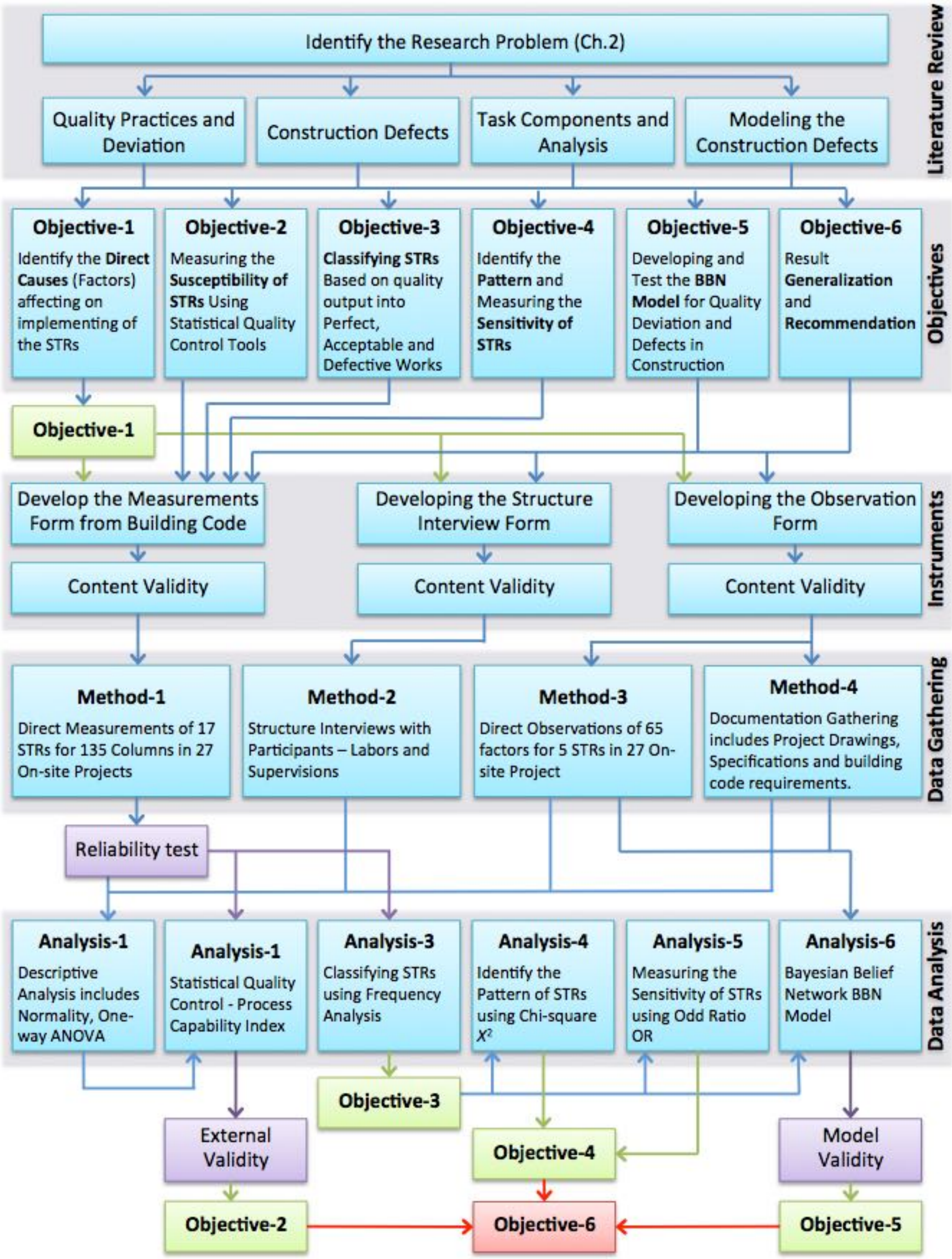


Figure 3.2 Research Methodology Flow chart

3.7 Case Study

As mentioned, a multiple-case design, or more specifically, an analysis of 17 case studies is applied. The advantages of a multiple-case approach are that the results are more likely to provide an outcome with a higher external validity and a lower exposure to observer bias depending on the collection and analysis techniques (Leonard-Barton 1988). A multiple-case design is said to be a useful approach when there is a need to capture complexity across a setting (Adams, Day & Dougherty 1998). To achieve methodological rigour, multiple-case designs should use replication logic (Yin 2003).

3.7.1 Case selection

The selection of cases should take into consideration theoretical and practical matters, such as contribution to knowledge and access to subject respectively (Silverman, 2005). To understand the cases being investigated in this study, it is convenient to review the levels of organisation with respect to construction activities. At the level of concrete structure members, columns are the compression members in construction concrete structures. The construction of columns involves a number of tasks, For example, "rebar" is one such task. The performance of "rebar" itself involves a number of sub-tasks. For example, "longitudinal bar fabrication" is one such sub-task. At this level, the sub-task level, each sub-task, such as "longitudinal bar fabrication" should adhere to specific requirements as provided in building codes. Each requirement, for the purposes of this study will be referred to as a sub-task requirement ('STR'). It is this sub-task requirement level that is of interest in this study. In other words, each sub-task requirement included in the study represents a case. As there are 17 sub-task requirements included in this study, there are 17 cases. The 17 sub-task requirements included in this study are sequential and are related the first two column tasks, these being, "rebar" and "framework".

The reasons this study focuses on the sub-task requirements of sub-tasks related to column construction are as follows:

- Columns are a very important member, as the compression members, of construction concrete structures. The tasks involved are some of the most difficult and important tasks of civil engineering (Tchidi, He & Yan, 2012).

This means that contractors will most likely demonstrate a commitment to high quality.

- Implementing the column's sub-tasks often takes short time (with average one week), making data collection from a range of cases convenient and rapid
- Similarly, for the above reason, the sub-tasks are accessible. Columns are a common feature of concrete buildings and are therefore easy to find
- Given that each construction structure has a number of different columns, the different dimensions will mean that the work carrying out by operatives is varied and not routine. This may mean that defects are caused by variety and that different variations can be compared. This follows Perry's (1998) advice that cases should be selected so that literal replication, namely, similar results due to predictable reasons, and theoretical replication, namely, different results also due to predictable reasons and included.

3.7.2 Number of cases

The number of cases, which is appropriate for a given study, depends on the actual aim of the study (Hamel et al., 1993). One approach for determining case number is theoretical saturation, the point where no new according to Glaser and Strauss (2009) the point where no new properties or relevant patterns emerge from the data. In this study, 17 cases (sub-task requirements) were selected for inclusion. This quantity was selected in order to cover a range of sub-task requirements so that patterns of deviation could be obtained. Similarly, it was decided that for each of the 17 cases (sub-task requirements) a number of measurements will be taken (n = 68 - 135). This reason for selecting this range of measurements was to ensure that a more reliable pattern of results could be obtained. The varying number of measurements relates to practical considerations for each sub-task requirement. As mentioned, Yin (2003) notes in order to achieve methodological rigour, multiple-case designs should use replication logic. It is also noted that each case in a multiple-case design should not be thought of as part of a sample but more correctly as another experiment. Thus, the results of the first case can be compared to the results of the results of the second case. Where two or more cases are shown to support the same theory, then replication of the results may be claimed. This is a known as a mode of generalisation, namely analytical generalisation according to Yin (2003).

3.7.3 Unit of analysis

The unit of analysis with respect to case study methodology refers to scope and scale of each case (Yin, 2003). As mentioned, in this study, the case, or unit of analysis, is a sub-task requirement. This level of unit of analysis represents a high preciseness compared to other studies in the field of defect occurrence in construction. This specific unit of analysis was chosen in order to attempt to show a connection between quality deviation, defects and the nature of the tasks involved in construction. As mentioned in the literature review, it is argued that studies to date have neglected the role of the nature of tasks generally in relation to defect occurrence and have also specifically neglected the sub-task requirement level.

3.8 Data Collection

3.8.1 Procedures used for data collection

The effectiveness of a study is significantly affected by the nature of data collection processes (Cavana et al., 2001). In this study each measurement for each case was conducted using a four-step procedure. Firstly, documentation was collected. This involved collecting information about design specifications in order to make comparisons with building code requirement for specific sub-tasks. The second step was for a structured interview to be conducted with of labor about their knowledge of sub-task requirement. The third step involved the researcher observing the work process. The fourth step was the direct measurement of the sub-task performance. These procedures are represented in the following figure, and are explained in more depth following.

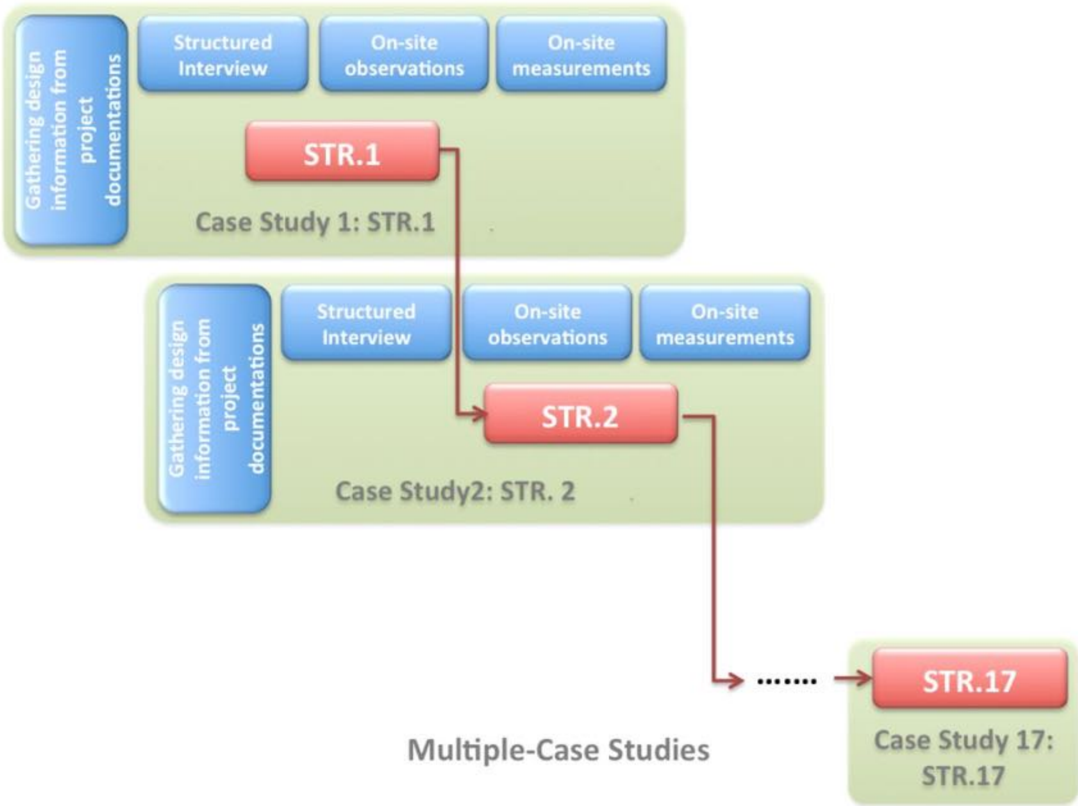


Figure 3.3 Data collection plan: Multiple-case studies

3.8.1.1 Documentation

Documentation is likely to be relevant to every case study according to Yin (2003). Records of information in the form of documents existing independent of the research process and may provide important insights into the participants or processes being studied (Morse and Richards, 2002). Here, information about design specifications was collected in relation to each measurement of each case in order to make comparisons with building code requirement for specific sub-tasks. This was conducted as a first step and before the labor starts the work for each STR (see Figure 3.3). The documents collected for design information included drawings, specifications and bill of quantity for all 17 STRs. The specific information, which needed to be recorded, related to the task's dimensions, quantity, and requirements generally.

3.8.1.2 Structured interviews

Structured interviews are a formal type of interviewing based on close-ended questions or items. This data collection tool is typically applied in quantitative studies where numeric data is collected (Yin, 2003). Here, structured interviewing of labor was the second step, and was conducted prior to labor commencing performance of each STR (see Figure 3.3). For each of the 17 STRs two structured interviews were conducted, one with the supervisors (e.g., project manager, quality manager or contractor), and another with labor, who performed the sub-task. Five questions relating to their knowledge of required dimensions, materials, equipment and so on were asked.

3.8.1.3 Observations

Observation is a common data collection method used in case studies. Observation is often referred to as being either non-participant, or direct, observation whereby the researcher observes the subject without interaction, and participant observation where the researcher participates in the relevant activity under observation (Yin, 2003). Having said this it is recognised that there are a range of combinations of the two types as the researcher's presence can be more or less overt (Morse and Richards, 2002). Here, direct observation of the performance of the sub-task was performed (see Figure 3.3). An observation schedule was adopted including items such as recording the task-resource factors and the workplace factors, labor performance, the supervisors performance, the usage of the materials, the usage of the equipment, the workplace condition either the weather or site condition, and commitment doing the work.

3.8.1.4 Direct measurements

Direct on-site measurements were conducted. This was the fourth and final step and was conducted at the completion of each sub-task performance (see Figure 3.3). Measurements include recording the dimensions of the actual work for each STR in order to compare it with the design specification and building code requirements.

3.8.2 Instrumentation for data collection

An inspection checklist and an structured interview/observation schedule were developed for the purposes of this research, namely, to measure quality deviation and to identify factors which may be relevant to the causation of deviation with respect to each STR (refer to Figure 3.1).

3.8.2.1 Inspection Checklist (direct measurement)

The inspection checklist (Appendix A) was developed to collect data relevant to the design and actual work on the project site(s). This checklist included multiple data sources from project documentations in drawings, specifications, and bills of quantities, two building code requirements (Saudi Building Code SBC-305A & B and American Concrete Institute Code ACI-318A & ACI-117). The two building codes were considered as it was noted anecdotally that the majority of organisations use the ACI code in lieu of the SBC (which was developed with reference to the ACI code).

The inspection checklist was used to collect research data. This work addressed multiple on-site cases studies, targeting 17 specific sub-tasks requirements (STRs) related to typical (concrete structure) compression members. The compression members analysed in detail for this research were archetypical column elements, with data generated through structured site-visits to 27 project locations in the city of Riyadh, Saudi Arabia, December 2013 to April 2014. Table 3.3 below lists the 17 STRs selected specifically for this study. The targeted measurements' range of tolerances and the maximum and minimum specification boundaries for each sub-task can be drawn from this data and thus, a future degree of deviation can be measured on-site.

Table 3.3 below details in column 1, the tasks for: (i) reinforcement-bar supply/installation; and, (ii) formwork (false-work) supply/installation. Table 3.3 also describes in column 2, the respective subtasks for (i) rebar, namely: longitudinal bar fabrication; installation of ties, stirrups and hooks, and, cage-assembly; and (ii) formwork subtasks of: shuttering; levelling; and, column installation/positioning. Table 3.3, column 3 describes the targeted Sub-Task Requirements (STR). Table 3.3, column 4 describes the minimum tolerance, lower-specification-limit (LSL). Table 3.3, column 5 describes the maximum tolerance, upper-specification-limit (USL).

Table 3.3 Building code requirements for the selected column's sub-tasks

Task	Sub-task	Sub-task requirements STR	Min. tolerance – LSL	Max. tolerance– USL
Rebar	Longitudinal Bars Fab.	STR.1: Steel cross-section area (A_{st}) [a & c]	$A_{st} = 0.01A_g$[a,c]	$A_{st} = 0.08A_g$
		STR.2: Bars Length: designed length x [a & c]	Designed length x (-50mm)	Designed length x (+50mm)
		STR.3: Lap splices [a & c]	x*0.83 (-25mm) or 300mm	x*0.83 (+25mm)
		STR.4: Bars Offset - longitudinal bars [a & c]	1 in 1 (Slope)	1 in 6 (Slope)
	Ties, Stirrups & Hooks	STR.5: Ties width: D [a & c]	$D \leq$ 200mm -10mm $D>$ 200mm -15mm	$D \leq$ 200mm +10mm $D>$ 200mm +15mm
		STR.6: Ties depth: d [a & c]	$d \leq$ 200mm -10mm $d>$ 200mm -15mm	$d \leq$ 200mm +10mm $d>$ 200mm +15mm
		STR.7: Ties: Hooks dimensions, Bar $\phi = x$ [a & c]	$x \leq 16\phi$ ($6d_b$ -15mm) $x = 20\phi - 25\phi$ ($12d_b$ -15mm)	$x \leq 16\phi$ ($6d_b$ +15mm) x=20ϕ-25ϕ ($12d_b$+15mm)
		STR.8: Ties Angular ^{o}, Bar $\phi = x$ [a, c & d]	$x \leq 25\phi$ (90^o or 135^o -2 ½ degrees) $x> 25\phi$ (90^o -2 ½ degrees)	$x \leq 25\phi$ (90^o or 135^o +2 ½ degrees) $x> 25\phi$ (90^o +2 ½ degrees)
		STR.9: Ties: Bend dimensions, Bar $\phi = x$ [a & c]	$x \leq 16\phi$ ($4d_b$ -25mm), $x = 16\phi$-25ϕ ($6d_b$ -25mm) $x = 28\phi$-36ϕ ($8d_b$ -25mm) $x> 40\phi$ ($10d_b$ -25mm)	$x \leq 16\phi$ ($4d_b$ +25mm), $x = 16\phi$-25ϕ ($6d_b$ +25mm) $x = 28\phi$-36ϕ ($8d_b$ +25mm) $x> 40\phi$ ($10d_b$ +25mm)
	Cage Assembling	STR.10: Horizontal spacing x [a & c]	$x \geq 1.5d_b$ or 40mm	$x \leq$ 150mm
		STR.11: Vertical spacing x_v [a & c]	x_v = $16d_b$, $48d_b$, or least column width (-25mm)	x_v = $16d_b$, $48d_b$, or least column width (+25mm)
		STR.12: Spacing above the slab x [a & c]	$x = 0.5 * x_v$ (-25mm)	$x = 0.5 * x_v$ (+25mm)
Form work	Formwork Shuttering	STR.13: Cross-sectional dimensions: width x [a, c & d]	$x \leq$ 30cm, -0.9525cm 30cm< $x \leq$ 90cm, -1.27cm $x>$ 90cm, -2.54cm	$x \leq$ 30cm, +0.9525cm 30cm< $x \leq$ 90cm, +1.27cm $x>$ 90cm, +2.54cm
		STR.14: Cross-sectional dimensions: depth x [a, c & d]	$x \leq$ 30cm, -0.9525cm 30cm< $x \leq$ 90cm, -1.27cm $x>$ 90cm, -2.54cm	$x \leq$ 30cm, +0.9525cm 30cm< $x \leq$ 90cm, +1.27cm $x>$ 90cm, +2.54cm
		STR.15: Concrete cover x [a & c]	$d \leq$200mm, x=40mm -10mm $d>$200mm, x=40mm -15mm BUT not less than 1/3 Cover	$d \leq$200mm, x=40mm +10mm $d>$200mm, x=40mm +15mm
	Formwork leveling	STR.16: Deviation from plumb for column x [d]	0.00	26m and less, x = 0.3% of high until max +2.5 cm
	Column positioning	STR.17: Deviation between horizontal items x [d]	$x>$ 30cm (12 in), x = -5cm	$x>$ 30cm (12 in), x = +5cm

Source: [a]SBC-A; [b]SBC-C; [c]ACI-318; [d]ACI-117

3.8.2.2 Structured interview/observation schedule

A structured interview/observation schedule (Appendix B) was developed to collect data relevant to task resource and workplace conditions. The structured interview/observation schedule developed consisted of 65 items placed into three sections, (1) items to be answered through structured interview; (2) items to be answered through direct observation of work process and workplace condition; and (3) items to be checked through review of project documentation.

The items for each section were developed based on a review of the literature related to defect occurrence. Prior empirical studies in this regard have focused on cause either direct or root causes (Busby & Hughes, 2004; Georgiou, 2010; Josephson & Hammarlund, 1999; Love P. E. et al., 2009; Sommerville, 2007; Tah & Carr, 2000; Tilley & McFallen, 2000); rework or consequences (Ayudhya, 2011; Chung, 1999; Fayek et al., 2004; Love P. E. et al., 2004; Tserng, et al., 2013); the modeling and prediction techniques (Love et al., 2002; Love et al., 2009; Cheng et al., 2015; Han, et al., 2012; Palaneeswaran et al., 2008); and the quality practices (Burati et al., 1992; Jafari & Love, 2013; Love & Edwards, 2004b; Tchidi, He, & Li, 2012).

The items were tested for content validity. This process involved judgment by a panel as described following in section 3.6.3.2.

Table 3.4 Direct Factors and Causes of the Quality Deviation and Defects

Direct Factors, Causes and Variables of the Quality Deviation			References
XB. Task Resource Factors			
1	XB.1 Worker-related underperformance Factors		
2		XB.1.1 Lack of knowledge	Josephson & Hammarlund, 1999, Burati et al., 1992, Hwang, 1995, Fayek et al., 2004; Lopez et al., 2010.
3		XB.1.1.1 Material size/type	
4		XB.1.1.2 Material quantity	
5		XB.1.1.3 Dimensions required	
6		XB.1.1.4 Tolerance required	
7		XB.1.2 Lack of commitment	Reason J. 2002, Love P. E. et al., 2004, Wang, Chan & Suen, 2005, Ayudhya, 2011, Diekmann & Girard, 1995, Burati et al., 1992, Abdul-Rahman, 1995, Fayek et al., 2004; Lopez et al., 2010.
8		XB.1.2.1 Communication with supervisory	
9		XB.1.2.2 Adherence to procedures	
10		XB.1.2.3 Adherence to design & standard (SBC)	
11		XB.1.2.4 Collaboration with Teamwork	
12		XB.1.3 Lack of experience	Kumaraswamy, 1997, Diekmann & Girard, 1995, Abdul-Rahman, 1995,

			Fayek et al., 2004.
13		XB.1.4 Lack of skills	Reason J. 2002, Love P. E. et al., 2004, Wang, Chan & Suen, 2005, Ayudhya, 2011, Davis et al., 1989, Kumaraswamy, 1997, Peña-Mora et al., 2003, Diekmann & Girard, 1995, Abdul-Rahman, 1995, Fayek et al., 2004; Lopez et al., 2010.
14		XB.1.4.1 Communication/language barrier	
15		XB.1.4.2 Handle with material/equipment	
16		XB.1.4.3 Well understanding of information	
17		XB.1.4.4 Work Accurately	
18	XB.2 Supervisor-related underperformance Factors		
19		XB.2.1 Lack of knowledge	Josephson & Hammarlund, 1999, Burati et al., 1992, Hwang, 1995, Fayek et al., 2004; Lopez et al., 2010.
20		XB.2.1.1 Material size/type	
21		XB.2.1.2 Material quantity	
22		XB.2.1.3 Dimensions required	
23		XB.2.1.4 Tolerance required	
24		XB.2.2 Lack of commitment	Reason J. 2002, Love P. E. et al., 2004, Josephson et al., 2002, Wang, Chan & Suen, 2005, Ayudhya, 2011, Kumaraswamy, 1997, Peña-Mora et al., 2003, Burati et al., 1992, Abdul-Rahman, 1995, Fayek et al., 2004; Lopez et al., 2010.
25		XB.2.2.1 Communication with labors	
26		XB.2.2.2 Adherence to procedures	
27		XB.2.2.3 Adherence to design & standard (SBC)	
28		XB.2.2.4 Excessive supervisory absenteeism	
29		XB.2.3 Lack of experience	Kumaraswamy, 1997, Diekmann & Girard, 1995, Abdul-Rahman, 1995, Fayek et al., 2004.
30		XB.2.4 Lack of skills	Reason J. 2002, Love P. E. et al., 2004, Wang, Chan & Suen, 2005, Kumaraswamy, 1997, Peña-Mora et al., 2003, Diekmann & Girard, 1995, Fayek et al., 2004; Lopez et al., 2010.
31		XB.2.4.1 Communication/Language barrier	
32		XB.2.4.2 Well understanding of information	
33		XB.2.4.3 Handle with Documents/Resources	
34		XB.2.4.4 Work Accurately	
35	XB.3 Materials-related problems Factors		Love P. E. et al., 2004, Josephson et al., 2002, Josephson & Hammarlund, 1999, Abdul-Rahman, 1995, Fayek et al., 2004.
36		XB.3.1 Materials availability	
37		XB.3.2 Inadequate quantity of material	
38		XB.3.3 Noncompliance with specification	
39		XB.3.4 Hard to deal with material	
40	XB.4 Equipment-related problems Factors		Josephson et al., 2002, Josephson & Hammarlund, 1999, Abdul-Rahman, 1995, Fayek et al., 2004.
41		XB.4.1 Equipment availability	
42		XB.4.2 Inadequate quantity of equipment	
43		XB.4.3 Noncompliance with specification	
44		XB.4.4 Hard to deal with equipment	
45	XB.5. Documentation-related underperformance Factors		
46		XB.5.1 Drawings-related underperformance	Love P. E. et al., 2004, Josephson et al., 2002, Wang, Chan & Suen, 2005, Ayudhya, 2011, Davis et al., 1989, Kumaraswamy, 1997, Peña-Mora et al., 2003, Fayek et al., 2004.
47		XB.5.1.1 Missing Information	
48		XB.5.1.2 Misleading/Clash information/details	
49		XB.5.1.3 Wrong Information	
50		XB.5.1.4 Unavailable documentations	

51		XB.5.2. Specifications-related underperformance	Love P. E. et al., 2004, Josephson et al., 2002, Wang, Chan & Suen, 2005, Ayudhya, 2011, Davis et al., 1989, Kumaraswamy, 1997, Peña-Mora et al., 2003, Diekmann & Girard, 1995, Fayek et al., 2004.
52		XB.5.2.1 Missing Information	
53		XB.5.2.2 Misleading/Clash information/details	
54		XB.5.2.3 Wrong Information	
55		XB.5.2.4 Unavailable documentations	
XC. Task Surroundings Factors			
56	**XC.1** Inappropriate surroundings conditions Factors		
57		XC.1.1 Inappropriate weather Factors	
58		XC.1.1.1 Temperature	Ayudhya, 2011, Peña-Mora et al., 2003, Diekmann & Girard, 1995, Semple et al., 1994, Fayek et al., 2004.
59		XC.1.1.2 Rain	
60		XC.1.1.3 Wind	
61		XC.1.2 Inappropriate site condition Factors	
62		XC.1.2.1 Crowded, Traffic, or Noise	Josephson & Hammarlund, 1999, Ayudhya, 2011, Peña-Mora et al., 2003, Diekmann & Girard, 1995, Abdul-Rahman, 1995, Fayek et al., 2004.
63		XC.1.2.2 Access to work location	
64		XC.1.2.3 Unforeseen ground–site conditions	
65		XC.1.2.4 External Uncertainty	

3.8.3 Content validity of the research instrumentations for collection the data

Content validity refers to the extent that the research instrument on its face appears to experts to be able to measure what it purports to measure (Polit & Beck, 2006). In this research, the inspection checklist (direct measurement) and structured interview/observation schedule were tested for their content validity through a process of expert consultation prior to commencing the data collection.

3.8.3.1 Expert consultation of inspection checklist

The target cases were specific requirements from column's sub-tasks, thus the checklist was developed based on the building code by the researcher, with support from his supervisor, both are civil engineers. The process of expert consultation also involved four face-to-face interviews with industry experts (three academic lectures from Curtin University and PhD student in Curtin University with 15 years' experience in the construction industry and building code) to discuss the content and form of the inspection checklist, with a specific focus to ensure the comprehensiveness and realistic of the instrument. The experts agreed with the proposed instrument for the purposes of measuring quality deviations and defects objectively. However, while the group agreed that deviation falling short of the minimum tolerance specifications would typically result in potentially catastrophic defect occurrence, two experts pointed out that deviation exceeding maximum tolerance specifications would result in wastage of materials, the creation of extra work, and exposure to cost overruns, but not necessarily the causation of unsafe defects. These recommendations were taken into consideration when drafting this dissertation.

3.8.3.2 Content validity of the structured interview/observation schedule form

A process of expert consultation was also conducted in relation to the structured interview/observation schedule form. Three expert were involved each of them academic lecturers; two from Curtin University and one from UAE University. Two face-to-face semi-structured interviews (open-ended questions) were undertaken with academic lectures from Curtin University and one email word document file with the lecturer from UAE University to evaluate the validity of the structured interview/observation schedule form. The interview was conducted through seeking the experts' responses to seven questions (shown in Appendix C). As a result of this process the number was reduced from 82 items to 65, and the wording of a very few items was added, deleted and revised. Overall, the content validity of the structured interview/observation schedule form for the purposes of measuring the quality deviations and defects was endorsed.

3.9 Data Analysis

Data analysis is this study adopted the conventional quantitative approach of exposing the data to statistical procedures. Descriptive statistical procedures and inferential statistics procedures were conducted.

3.9.1 Descriptive statistics & data preparation

Descriptive statistical procedures are used typically to summarise data sets to enable them to be read and interpreted more easily. Descriptive statistical procedures involve the use of different multi-item scales. In this research mean, descriptive statistical procedures were conducted with respect to the demography and frequency of the data collected. Numeric statistical procedures were conducted to evaluate the extent that the data sets were robust and sensitive against assumptions of outliers and normality. One-way ANOVA was used to measure the consistency of the data collected. Pedhazur (1997) notes that in situations when violations of assumptions exist, extracted understanding and knowledge under these cases are vulnerable to serious biases and may reduce the validity and credibility of results.

3.9.2 Data analysis / inferential statistics

Inferential statistics are used to test the statistical significance of the results that have been obtained from descriptive statistical procedures. Inferential statistical procedures are used to enable the researcher to gain awareness of the data set through testing central tendency and dispersion, to test data reliability and validity, and to test the proposed research model (Sekaran, 2003). Inferential statistical procedures in this sense are used to support or refute the existence of a generalisable phenomenon.

In this research, a number of inferential statistical procedures were applied to meet the objectives of the investigation. The first of these was a capability process index analysis, a statistical process control tool. This analysis assumes normal distribution of the process output. The analysis seeks to determine the capability of a process C_p and C_{pk}, which is a statistical index referring to process performance based on pre-set specific requirements. Capability process index analysis is a process based on calculations, which are used to evaluate if a system is capable of meeting a set of requirements or specifications. It is an analysis, which can be used to represent process improvement. Capability analyses are able to summarize information, show process capability, show required improvement, and show whether such improvement was achieved. Here, the susceptibility of each STR to exposure to quality deviation was identified and statistical process control amounts C_p and C_{pk} were employed to measure quality practices as described in Chapter 6.

Chi-Square (χ^2) Test of Contingencies - Pearson Chi-Square χ^2 & Cramer's V was another inferential statistical procedure conducted as part of this study. Chi-Square (χ^2) analysis is used to investigate association between two or more categorical variables. In this research, Chi-Square (χ^2) analysis was used to determine the association between the degree of deviation and the STRs as described in Chapter 7. The use of odds ratio analysis in this study is also described in Chapter 7. Odds ratio analysis is flexible and robust statistical parameter of how strongly are two variables related. Therefore, it quantifies the variable relationship strength or the effect size in a similar manner to Pearson correlation coefficient analysis. It is also used to evaluate ratio between odds of an outcome occurring to the odds of it not occurring. In this research, odds ratio analysis was used to rank the sensitivity degree of all STRs.

Finally, a BBN approach is used to quantify the most significant causes through observing and predicting of the interaction between the deviation level in terms of the quality practices for each STR (five STRs will be examined: STR.1, STR.5, STR.13, STR.15 and STR.16) and which kind of causes that related to the deviation for each STR. This method will be discussed further in Chapter 7.

3.10 Statistical Validity and Reliability

Quality criteria are typically applied to establish the appropriateness of any empirical research.

3.10.1 Content validity

Being a quantitative study, this investigation applied tests of content validity (as mentioned previously), external validity, and reliability. The content validity, as mentioned, involved two processes of expert consultation, one for each of the data collection instruments, namely, the inspection checklist and the structured interview/observation schedule form.

3.10.2 External validity

External validity tests are concerned with "knowing whether a study's finding can be generalised beyond the immediate [investigation]" (Voss et al., 2002). In other words, the extent that the findings of a study are applicable to other cases is the focus of tests of external validity. Generalisability is typically divided into the statistical generalization, which is dependent on the sample size, and analytical generalisation, which is dependent on the number of cases (Yin, 2003). This study aimed to achieve statistical generalisation with respect to STR deviation through the use of statistical process control analysis, specifically the capability of a process C_p and C_{pk}, and analytical generalisation with respect to the model proposed based on the use of Bayesian Belief Network.

3.10.3 Reliability

Reliability refers to the reproducibility of the study. As Voss et al. (2002) it is “the extent to which a study’s operations can be repeated, with the same results.” Reliability is a concept related to consistency as it is assumed that where a test is reliable free of errors and bias, the repetition of the test will yield similar results (Yin, 2003). The lower the variation that an instrument produces application to application the higher the reliability (Polit and Hunger, 1985). In this study, measurements from five different columns were obtained for each of the projects involved. For each setting, three sets of measurements were taken on the first day and two measurements were taken the following day. The measurements collectively were then statistically analysed using Spearman test to evaluate consistency.

3.11 Chapter Summary

The chapter described that due to a focus on observation and measurement, the study adopted a post-positivism claim of knowledge and quantitative strategy of inquiry. The chapter discussed the rationale for the use of multiple case studies in order to examine the sensitivity of STRs and to simulate the interaction of direct causes and sensitivity degree for each STR. The chapter discussed how the research instruments to collect data set included collecting information about design specifications from the building code requirement, structured interview, direct observing the work process and the direct measurement to address the objectives of the study. Finally, the data analysis methods and tests of statistical validity and reliability that employed in the research have been described.

CHAPTER 4: Data Preparation

4.1 Chapter's Purpose and Framework

The purpose of this chapter is to present the data screening procedures. This is a preliminary data management stage towards conducting additional specific analyses. Section 4.2 provides details of data collected relevant to the sites and instruments included in the project, namely an inspection checklist measurements and a structured interview/observation schedule. Section 4.3 outlines the data screening methods adopted in this study for the purposes of ensuring the data sets were appropriate and ready to use. This involved examining data set normality, outliers, standard deviation and standard error. Section 4.4 presents numerical descriptive statistics, and interprets these results for the purposes of the objectives of the study. Section 4.5 describes the application of a one-way analyses of variance (ANOVA) testing to determine the existence of significant differences between the means of two independent categories in single sample. Finally, Section 4.6, presents the results of data reliability tests, and Section 4.7 provides a summary and the main conclusions of the chapter.

Data preparation concerns ensuring collected data's scientific quality. Data preparation processes will be applied to serve a number of purposes. Firstly, the processes should aim at ensuring that the effect of any missing data is limited. Secondly, extreme outlier values (those far away from the mean distribution) should be eliminated. Thirdly, processes should ensure the assumption of normal distribution for each sample will be upheld. And finally these processes should go towards ensuring that deviation of the mean value of different categories within specific sample is limited. Such constraints are necessary in order to apply univariate and multivariate analyses (Capability process index, Chi-square, Odd ratio and Bayesian belief network). In this study, data analysis processes were conducted by IBM® SPSS® Statistical Standard Grad Pack Version 22.0, Matlab® 2013a, BayesiaLab® 5.3, and Minitab® 17.

4.2 Descriptive of the Instrumentation for Data Collection

This section provides details of data collected relevant to the sites and instruments included in the project, namely an inspection checklist measurements and a structured interview/observation schedule. As mentioned in Chapter 3, an inspection checklist (direct measurement) was developed and data was collected relating to project documentation, which involved collecting information about design specifications in order to make comparisons with building code requirement for specific sub-tasks and the direct measurement of the sub-task performance. A structured interview/observation schedule was also developed and data collected through structured interviews conducted with labor about their knowledge of sub-task requirement and observations of the work process.

Data was collected for 8 hours a day and two projects were visited per week between December 2013 and April 2014. The geographical setting was Riyadh, the capital city of Saudi Arabia, and in total 27 residential building projects were included in the study. At each the residential building projects, 5 columns (a compression member in construction concrete structure) of a variety of dimensions were selected. Non-uniform columns were selected to generate a rich database. In total, 135 columns were selected.

4.2.1 Inspection Checklist (direct measurement)

The inspection checklist was concerned with items specific to 17 STRs (see section 3.6.2.1 in Chapter 3). These requirements were sourced from the Saudi Building Code (305A&B) and American Concrete Institute Code (ACI-318A & ACI-117). Performance of the sub-task was compared to its corresponding requirements and design specifications where relevant. See Table 4.2. In total, 3030 sub-task events (17 STRs × 135 columns) were measured. The inspection checklist was completed onsite for each sub-task event by the principal researcher.

The number of sub-task events that were measured for each of the sub-task requirement is present in the following figure (Figure 4.1). As can be seen while STR 4 was only measured 68 times, STR 15 was measured on 516 occasions. The variation was a result of the quantity of sub-tasks available to be measured in each column. While STR 4 (off-set bar) was not measurable in every column, STR 15 (concrete cover) was able to be measured multiple times for each column.

The following figure (Figure 4.2) presents the number of projects in which each STR was able to be measured. The majority of STRs were measurable in at least one of the columns for each of the sites. Figure 4.3 presents the proportion of projects that were apartments construction projects (14 from 27) and the number that were villas construction projects (13 from 27). The projects included in the study were found to have either permanent inspectors onsite or temporary inspectors who would visit weekly or fortnightly. Permanent onsite inspectors were associated with apartment construction (Figure 4.4).

4.2.2 Structured Interview/Observation Schedule

A 65-item structured interview/observation schedule was developed. The items were organised into sections, namely, items (n = 5) to be answered through structured interview (workers concurrently asked questions concerning their understanding of specific STR protocol and the worker's expectance); items (n = 5) for supervisors (quality managers and/or inspectors); items (n = 8) to be checked through review of project documentation and the remaining items (n= 43) to be answered through direct observation of work processes and workplace conditions (see Table 4.1).

The researcher initially used the schedule to investigate each of the 17 STRs, and to apply the results of the investigation to the BBN model (as described following in Chapter 7). The immense complexity of the analysis suggested that using a restricted number of STRs would be favourable for the purposes of understanding the STR-by-STR interactions. The researcher analysed nine STRs and found that the results were still too voluminous for meaningful publication. Finally, the researcher decided that an investigation of five out of the 17 STRs would provide a satisfactory demonstration of the proposed model. This sample size was considered to appropriate given the complexity of the networks involved, the purposes of the study and the need to attain sufficient data saturation (Glaser & Strauss, 2009; Hamel et al., 1993). The results for STR.1, STR.5, STR.13, STR.15, and STR.16 are shown following in Chapter 7 (see Figure 7.12).

It can be noted in Table 4.1 that the descriptive data for STR.13 involved 65 factors consistent with the 65-item schedule. The other four STRs included less than 65 factors due to the fact that only related or direct factors were included in the schedule for those STRs. Descriptive data for STR.1 included 60 factors as equipment-related factors (n = 5) were not applicable to this STR. Similarly, STR.5, STR.15, and STR.16 contained less than 65 factors as material-related factors (n = 5) were not applicable to these STRs.

Table 4.1 Data Descriptive structured interview/observation schedule

	STR.1	STR.5	STR.13	STR.15	STR.16
Number of factors	60	60	65	60	56
Number of projects	27	27	27	27	26
Number of columns	131	134	131	135	130

This study includes multiple-case studies where each case study includes 135 samples. According to Collins et al. (2006), the minimum sample size suggestion for a causation study is 64 samples; however, this study includes 135 samples, which is sufficient to meet the minimum requirements.

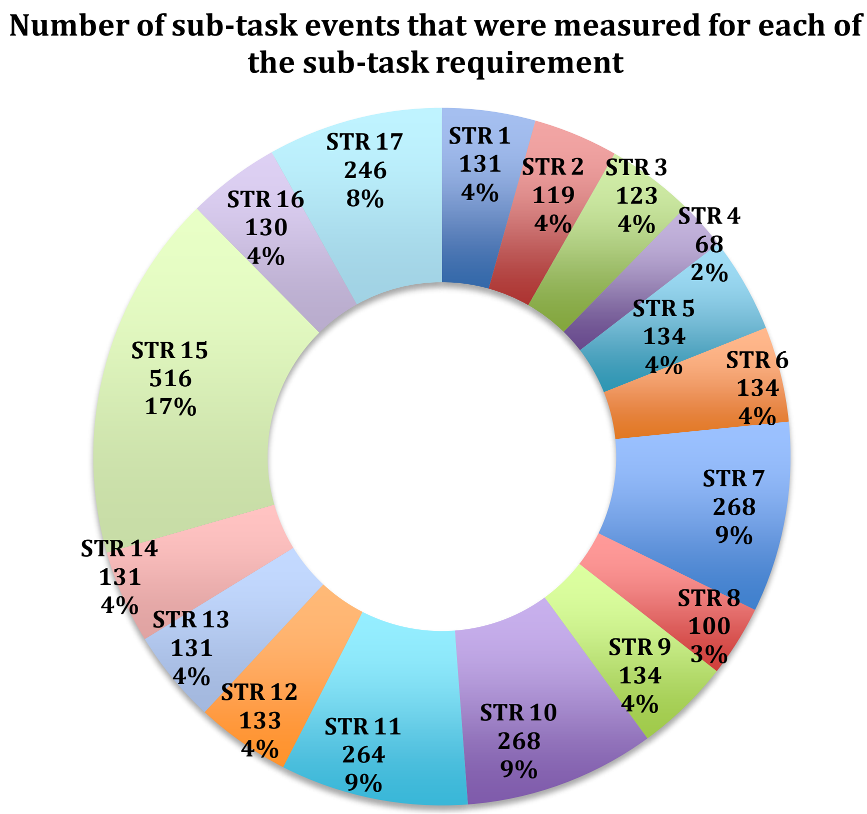


Figure 4.1 Pie chart for number of sub-tasks requirements.

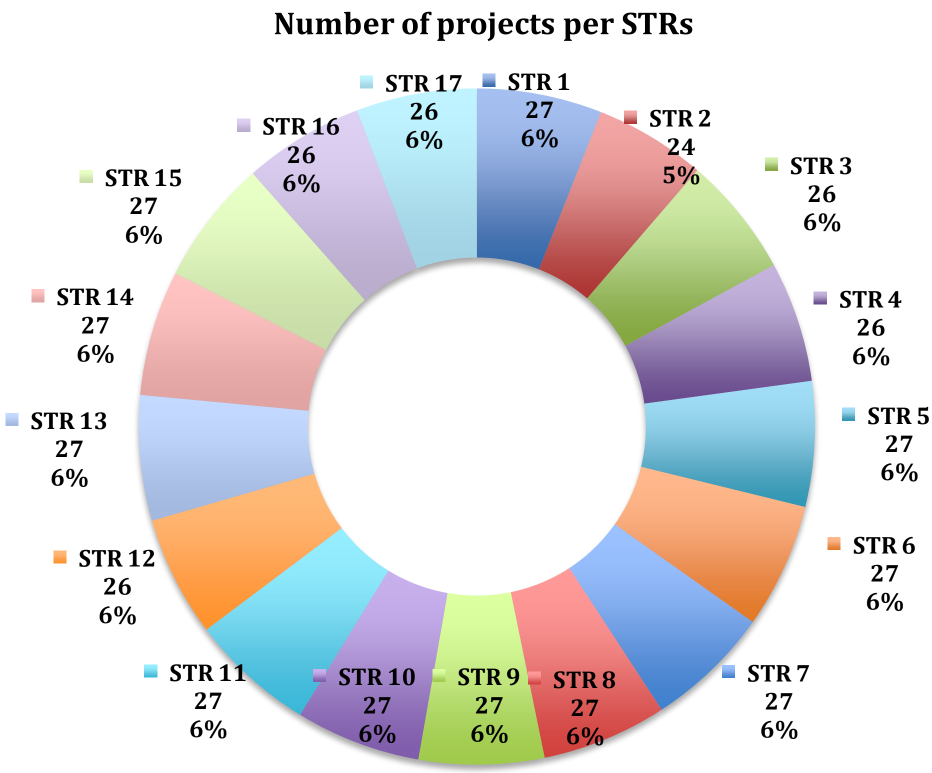


Figure 4.2 Pie chart for number of projects per sub-task requirement

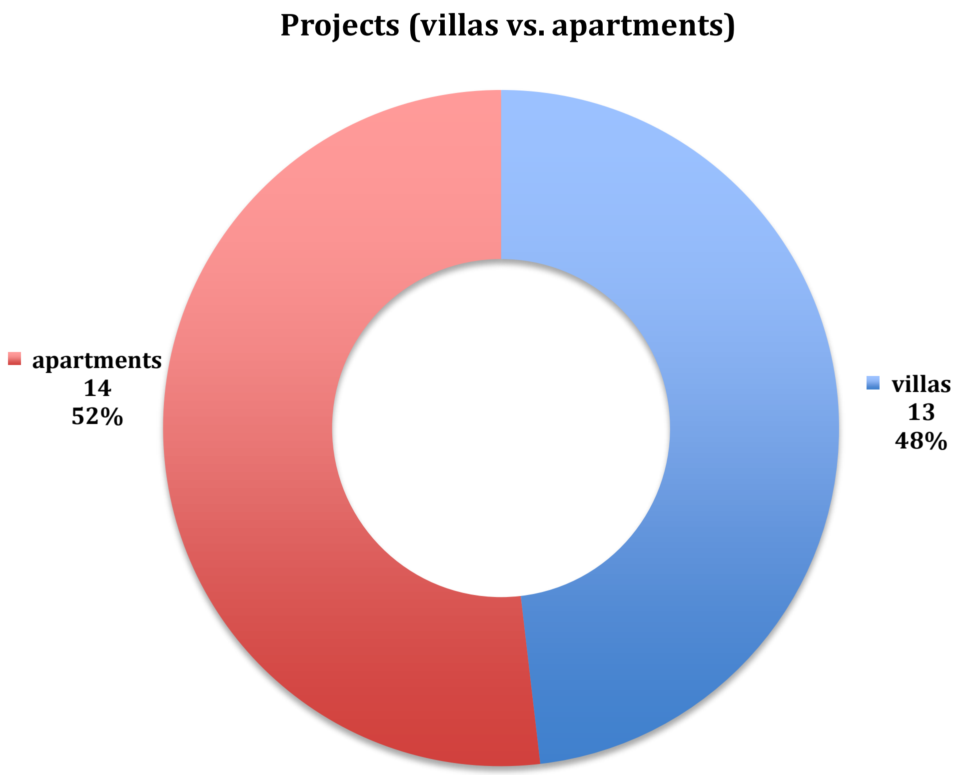


Figure 4.3 Pie chart for villas vs. apartments

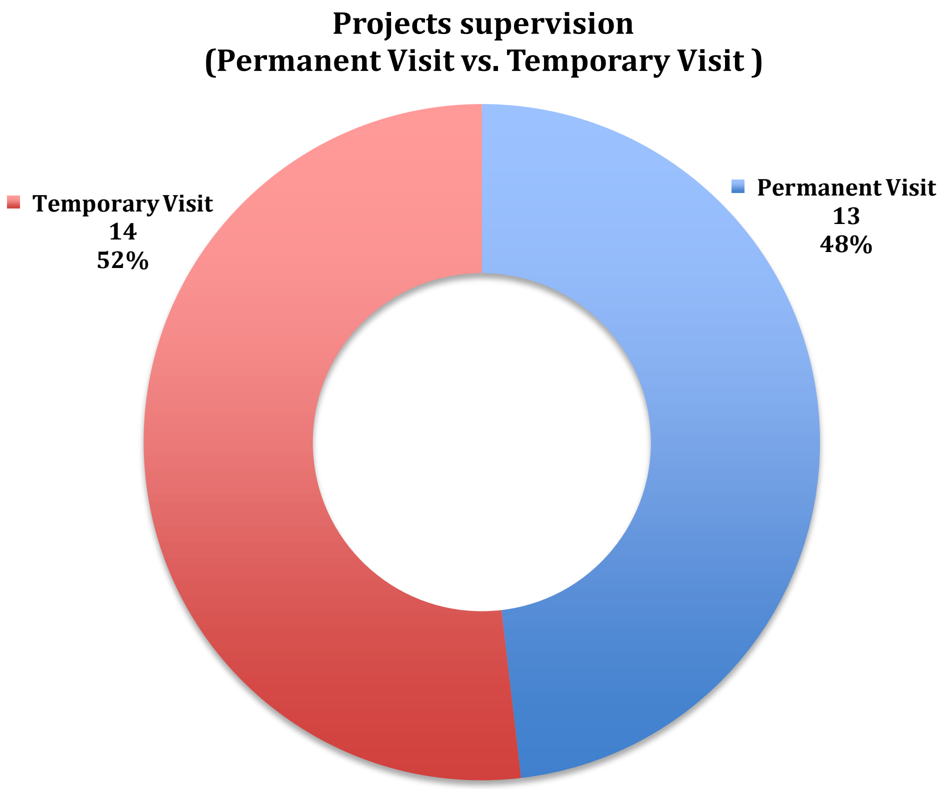


Figure 4.4 Pie chart for project supervision types

4.3 Data Numerical Descriptive Statistics

Statistical analysis processes can be applied to ensure the sensitive and robustness of the data set against assumptions of normality, outlying cases and missing values of samples. Where violations of such assumptions are found, bias may be present undermining the validity of the data and the credibility of conclusions (Pedhazur, 1997). Thus, it is critical to screen data sets for quality through an evaluation of the distribution of variables. (Kline, 2005; Tabachnick & Fidell, 2007).

Two data collection instruments were numerical examined. The first was an "Inspection Checklist (direct measurement)" and the second was a "Structured Interview/Observation Schedule".

4.3.1 Numerical Descriptive of Inspection Checklist (direct measurement)

4.3.1.1 Test normality of data set

An assessment of the normality of data is a fundamental test determining whether necessary assumptions exist in parametric testing for normal data. In the current study, an assessment of the normality of data is also conducted to test the normality of sub-tasks requirements practices at projects sites. Normality evaluation can be performed either statistically or visually. Visual screening of normality through displaying and checking data distribution can helped with judging the assumption of normality of the data set (Pallant, 2010). The histogram is a popular visual screening methods used to check normality. Data may be considered as a normal distribution where the data represented as an appropriate bell-shaped curve. A P-P plot is another method. Data may considered as a normal distribution where the data represented as a straight diagonal line. Another method is the boxplot. Data may considered as a normal distribution where the data represented as a symmetric boxplot with the median line and the as a symmetric edges (Pallant, 2010). However, boxplot is considered unreliable as it fails to ensure appropriate and precise distribution of the data set.

In more effective and efficient modality, two statistical techniques, which are skewness and kurtosis, are vastly used to evaluate the assumption of normality (Allen & Bennett, 2012). The concept behind skewness technique is to assess the degree of the symmetry of the probability distribution, where the mean of the variable is skewed from the center of the distribution (Allen & Bennett, 2012; Hair et al., 2006). Whilst, the concept behind kurtosis technique is to assess the peakedness of the distribution, which evaluates the shape of the normal distribution of the data either it is peaked or flat shape (Hair et al., 2006; Tabachnick & Fidell 2001). The values for both skewness and kurtosis relative to the data should be equal to zero to be considered as an ideal case of the normal distribution (Tabachnick & Fidell 2001). However, to ensure the normality of the data distribution, the index values for both skewness and kurtosis relative to the shape of the distribution should fall between the critical values of ±1.96 (Tabachnick & Fidell, 2007). The index values that are greater than the critical value of ±1.96 for univariate seems they have serious problem related to the data distribution.

Through screening the distributions of data set visually via histogram, P-P plot and boxplot, it is seemed that all data for the sub-tasks requirements roughly are well distributed. The bell-shaped curve of the histogram, straight diagonal line for P-P plot and symmetric of the median line and edges of the boxplot of the majority of the univariate had an appropriate distributions and were significantly normal and for the rest univariate almost convenient. On the other hand, the results show that all skewness and kurtosis values for all regions fall between the recommended critical values of ±1.96 (see Table 4.2). Consequently, the visual inspection and results of all the univariate of the data set prove and justify the necessary assumption of normality of the distribution of the data set. Furthermore, promote using the data set for further statistical analysis.

4.3.1.2 Outliers screening

Outliers are observations within a data set that are essentially different and significantly deviates from the rest of the observations scores (Hair et al., 2006).

According to (Tabachnick & Fidell, 2007), the outliers' cases might occur due to four causes: 1) data-entry mistakes; 2) Insert the missing values in calculations; 3) data-collection mistakes by researcher; and 4) collecting an anomalous or rare data from source. Cases one and two have been avoided through review the data frequently during data analyses, while a few cases identified in this study related to the case four due to quality practices in project site.

Therefore, screening the outliers within data set is an essential procedure due to the research results are highly influenced by very few deviated values within the data that may bias the mean of distribution from the true value (Field, 2009). Univariate outliers, which are outliers that occur within a single variable, are detected by inspecting all the cases that exist at outer areas of the distribution with values more than three standard deviations (Hair et al. 1998; Kline, 2005). Univariate outliers can be calculated by converting all the values of the univariate into standardized z-scores and then check the absolute value of z-scores (|z|) (Tabachnick & Fidell, 2007). If the absolute value is greater than 3.29, this means the value exist at outer areas of the distribution and considered as univariate outliers.

In this research, all observations of the 17 univariate were investigated against univariate outliers. The standardized z-scores were examined for the entire values of all the sub-tasks requirements. All absolute z-scores were found under the critical value 3.29 that means the data set are free for all 17 univariate outliers (see Table 4.2). Consequently, the data set is appropriate for further analyses.

4.3.1.3 Standard deviations and standard errors of the mean

Standard deviation (SD) and standard error (SE) of the mean are common indices used to estimate the variation and variability of random samples. SD estimates the extent that variation in a random sample within specific variable may effectively represent the mean of that variable through computing the amount of spread values around the mean (Field, 2009). If the SD value is large, the implication is that values within random sample spread widely around the mean. In contrast, an appropriate mean will be represented by a small value, which is indicative of less spread of values within random sample.

SE estimates the extent an individual sample within specific variable may effectively represent the population of that variable. SE is measured through dividing the SD by the square root of the sample size (n) (Field, 2009). If SE value is large, the implication is that the variation between individual samples within specific variable is high. In contrast, a good population will be represented by a small SE value, which is indicative of limited variation (Field, 2009).

Generally, in this research, SD and SE results indicate appropriate values in all but a few cases. The few cases are investigated in Chapter 5 using quality process control analysis. Numerical descriptive analyses results for all STRs are presented in Table 4.2.

Table 4.2 The numerical descriptive analyses for all the sub-tasks requirements

	Variables/Tasks: Description	Cases with $\lvert \boldsymbol{z} \rvert > 3.29$	Mean	SD	SE	Skewness	Kurtosis
1	STR. 1 - Sub-task requirement 1	0.0%	0.0128	0.00277	0.00025	0.4101	-1.7448
2	STR. 2 - Sub-task requirement 2	0.0%	0.0094	0.03218	0.00295	-0.3378	0.5432
3	STR. 3 - Sub-task requirement 3	0.0%	9.9479	18.0697	1.65645	0.04955	1.1772
4	STR. 4 - Sub-task requirement 4	0.0%	0.1300	0.11131	0.01350	1.9278	-0.9059
5	STR. 5 - Sub-task requirement 5	0.0%	-0.3377	0.66351	0.06214	-1.2035	-0.2962
6	STR. 6 - Sub-task requirement 6	0.0%	0.0149	0.48255	0.04169	-1.5072	0.8990
7	STR. 7 - Sub-task requirement 7	0.0%	1.9765	2.39070	0.15212	1.5419	0.8770
8	STR. 8 - Sub-task requirement 8	0.0%	1.0297	2.53042	0.25561	1.8975	0.2381
9	STR. 9 - Sub-task requirement 9	0.0%	-0.8082	0.80076	0.06917	1.9043	-0.9615
10	STR.10 - Sub-task requirement 10	0.0%	12.652	3.51342	0.21542	-0.5168	1.2449
11	STR.11 - Sub-task requirement 11	0.0%	17.031	2.07156	0.12823	0.7285	-0.0033
12	STR.12 - Sub-task requirement 12	0.0%	6.8370	4.01266	0.35890	-1.2074	-1.8488
13	STR.13 - Sub-task requirement 13	0.0%	0.9466	2.61944	0.22886	0.5283	1.8286
14	STR.14 - Sub-task requirement 14	0.0%	0.1667	0.49647	0.05851	1.2191	1.8265
15	STR.15 - Sub-task requirement 15	0.0%	0.3300	1.46396	0.06323	1.5377	-1.9052
16	STR.16 - Sub-task requirement 16	0.0%	0.2965	0.23205	0.02164	1.9336	-1.7561
17	STR.17 - Sub-task requirement 17	0.0%	0.4193	3.10761	0.19935	-0.0705	0.7235

4.3.2 Numerical descriptive of structured interview/observation schedule

4.3.2.1 Determining the missing values

Only the assessment of missing values is presented in the following chapter. The researcher used data set generated from the structured interview/observation schedules for BBN analysis, an approach appropriate for nonparametric data and for multivariate analyses (Conrady & Jouffe, 2011c). The statistical analyses of the numerical descriptive of the data collected from the structured interview/observation schedules are discussed following in Chapter 7 and 8.

The assessment of missing data is an important step for empirical researchers (Conrady & Jouffe, 2011c; Kline, 2005). The current study avoided the omission of data through reinforcing the purposes of the study and through continuous review of data gathering forms. There were no missing values identified. An assessment of missing data for STRs used for the proposed model is outlined in Table 4.3.

Table 4.3 Assessment of Missing value for Structured Interview/Observation Schedule

	STR.1	STR.5	STR.13	STR.15	STR.16
Number of factors	60	60	65	60	56
Number of columns	131	134	131	135	130
Missing Values	0.0%	0.0%	0.0%	0.0%	0.0%

4.4 Discussion of the Initial Findings of the Numerical Descriptive Statistics

The numerical descriptive analyses presented in Table 4.2 indicates data set quality. The data set satisfied several assumptions of normality of samples and supported visual inspection of distribution for each STR. Further initial findings can be extracted from Table 4.2. It can be noted that the degree of the tolerance of each STR impacts on the mean values. Moreover, the various designs of columns in the 27 different projects appear to contribute to forming the mean values.

The mean values vary across the 17 STRs and the boundary values ranged between 0.0094 and 17.031. One interpretation of the finding is that the tolerance for each STR varies based on the Saudi Building Code (SBC) and American Concrete Institute (ACI). Another interpretation is that the sub-task design for each column varies across the gathered samples. The mean values of STR.11, STR.10, STR.3, and STR.12, were 17.031, 12.652, 9.9479, and 6.8370 respectively, and were high compared to the other STRs.

The required tolerance values for these four sub-tasks requirements were also high compared to the values of the other STRs. Similarly, SD values for the four were also high at 2.07156, 3.51342, 18.0697, and 4.01266 respectively for STR.11, STR.10, STR.3, and STR.12. The SD value for STR.3 at 18.0697 was very high. These findings are discussed further in the following chapter (see Section 5.3). Some STRs with high tolerance values featured more moderate SD such as STR.17, and STR.2, which had values of 0.4193, and 0.0094 respectively.

STR mean values generally fell between the required tolerance values. The exceptions were STR.3 and STR.12 with means outside of tolerance. These cases are discussed further in the following chapter (see Section 5.2). The majority of STR mean values fell on the positive side of tolerance values except for STR.5 and STR.9 which were found to have mean values falling on the negative side.

4.5 ANOVA Analysis of the Data Quality Examination

It is important to investigate sampled-data relationships with the aim of identifying differences in the ways data was gathered. As mentioned previously (see Section 4.2.1), data was gathered from two types of residential buildings, namely, villas and apartments. An important difference between villas and apartments tended to be supervision patterns on site with the former tending to feature periodic (i.e., temporary) supervision and the latter featuring permanent supervision. A one-way analysis of variance (ANOVA) was used as part of a statistical comparative analysis for these differences and to examine the means equality and reliability of the data set.

One-way ANOVA enables the researcher to test population equality between two or more sample means for a specific categorical variable through the use of variances. The variance ratio (F statistic or Fisher statistic) of the overall test indicates whether a significant difference between the means exists. A significant difference is likely to exist where F statistic is larger than 1 (F>>1). F statistic output can also be examined using a statistical test for significance (P-value). A significant difference between groups is likely to exist when P-value is less than α: 0.05 ($P < 0.05$). In such cases, the sample size must be taken into account (Yin, 2009).

The effect size η^2 (Eta squared) is used to measure the extent the independent variable (IV) has affected the dependent variable (DV). The effect size η^2 (Eta squared) equals the treatment Sum of Squares (between groups) divided by the total Sum of Squares. If the value of the effect size $\eta^2 < 0.014$, the effect size is assumed small; $\eta^2 \geq 0.014$, the effect size is assumed medium; or if $\eta^2 \geq 0.059$, the effect size is assumed large (Cohen, 1988; Pallant, 2010). Typically, the effect size η^2 (Eta squared) will be small. In the case of significant difference between the groups, F statistic value is often of little practical importance.

The normality test and homogeneity of variance are important pre-requisite assumption that should be satisfied before conducting an ANOVA test. The normality test was satisfied and discussed previously (see Section 4.3.1.1.) Homogeneity of variance means "there should be an approximately equal amount of variability in each set of sources" (Allen & Bennett, 2012). The assumption of homogeneity of variance of ANOVA test has been violated where the value of the Levene's statistic is less than α: 0.05 ($P < 0.05$) (Berenson, et al., 2012).

The assumption of homogeneity was examined. The value of Levene's statistic was found to be greater than α: 0.05 ($P > 0.05$) for the STRs, suggesting the assumption of homogeneity of variance of ANOVA test has been satisfied. The ANOVA test results per type of residential buildings, namely villa ($n = 13$) and apartment ($n = 14$) are presented in Table 4.4. No STR was found to have a significant value of F statistic. Additionally, the statistical test (P-value) for significance indicated no significant difference existing between groups. The implication is that the ΔMean values were reasonable and the effect size was generally small with the exception of STR.3, which exhibited a slight difference between villas and apartments (with the ΔMean value of 6.1728).

Similarly, results based on supervision pattern differences, namely, periodic (i.e., temporary) (n = 14) and permanent (n = 13) are presented in Table 4.5 and indicate that no STR had a significant value of F statistic. Additionally, the statistical test (P-value) for significance indicated that there was no significant difference between groups. Again the implication is that ΔMean values were reasonable and the effect size was small with the exception of STR.3, which exhibited a slight difference between periodic and permanent supervision (with a ΔMean value of 5.6729).

It was found that only STR.3 had a slight difference on two ANOVA tests. The causation could be design problems, quality practices (violation the requirements) or/and the STR itself. The investigation of the result using SPC analysis is discussed in the chapter following (Chapter 5).

Table 4.4 The numerical descriptive analyses for buildings types

	Variables/Tasks: Description	Homogeneity of Variances	*F*	Sig.	Mean		Δ Mean	η^2
					Apartment	Villa		
1	STR. 1 - Sub-task requirement 1	0.371	0.415	0.521	0.012596	0.012918	0.000321	0.003
2	STR. 2 - Sub-task requirement 2	0.084	3.041	0.084	0.0046	0.0148	0.0102	0.025
3	STR. 3 - Sub-task requirement 3	0.187	3.544	0.062	13.1121	6.9393	6.1728	0.029
4	STR. 4 - Sub-task requirement 4	0.665	3.157	0.080	0.1213	0.0786	0.0427	0.046
5	STR. 5 - Sub-task requirement 5	0.531	3.719	0.056	-0.2193	-0.45610	0.2368	0.032
6	STR. 6 - Sub-task requirement 6	0.894	1.540	0.217	0.0643	-0.0391	0.1034	0.012
7	STR. 7 - Sub-task requirement 7	0.055	3.656	0.057	1.6765	2.2555	0.5790	0.015
8	STR. 8 - Sub-task requirement 8	0.192	0.706	0.403	1.2008	0.7595	0.4413	0.007
9	STR. 9 - Sub-task requirement 9	0.255	3.795	0.054	-0.6863	-0.9541	0.2678	0.028
10	STR.10 - Sub-task requirement 10	0.803	3.192	0.075	12.2796	13.0465	0.9823	0.012
11	STR.11 - Sub-task requirement 11	0.068	1.776	0.184	17.1893	16.8471	0.3422	0.007
12	STR.12 - Sub-task requirement 12	0.072	1.163	0.283	7.1743	6.3935	0.7808	0.009
13	STR.13 - Sub-task requirement 13	0.893	1.657	0.200	1.2209	0.6318	0.5891	0.013
14	STR.14 - Sub-task requirement 14	0.369	0.025	0.875	0.1750	0.1563	0.0187	0.000
15	STR.15 - Sub-task requirement 15	0.990	1.019	0.313	0.3911	0.2633	0.1278	0.002
16	STR.16 - Sub-task requirement 16	0.157	3.465	0.065	0.2603	0.3404	0.0801	0.030
17	STR.17 - Sub-task requirement 17	0.054	0.234	0.629	0.3316	0.5255	0.1939	0.001

Table 4.5 The numerical descriptive analyses for supervisory styles

	Variables/Tasks: Description	Homogeneity of Variances	*F*	Sig.	Mean		Δ Mean	η^2
					Visit	Permanent		
1	STR. 1 - Sub-task requirement 1	0.054	3.736	0.056	0.012362	0.013328	0.000966	0.030
2	STR. 2 - Sub-task requirement 2	0.064	0.286	0.594	0.0110	0.0079	0.0031	0.002
3	STR. 3 - Sub-task requirement 3	0.066	2.800	0.097	7.8027	13.4756	5.6729	0.023
4	STR. 4 - Sub-task requirement 4	0.071	2.512	0.118	0.1531	0.1106	0.0425	0.037
5	STR. 5 - Sub-task requirement 5	0.115	2.669	0.105	-0.4333	-0.2315	0.2018	0.023
6	STR. 6 - Sub-task requirement 6	0.356	0.061	0.806	0.0063	0.0273	0.021	0.000
7	STR. 7 - Sub-task requirement 7	0.733	3.673	0.056	2.2300	1.6449	0.5851	0.015
8	STR. 8 - Sub-task requirement 8	0.791	2.847	0.095	0.6279	1.4839	0.856	0.029
9	STR. 9 - Sub-task requirement 9	0.055	2.017	0.158	-0.8899	-0.6909	0.199	0.015
10	STR.10 - Sub-task requirement 10	0.419	4.247	0.040	12.9940	12.0830	0.9110	0.016
11	STR.11 - Sub-task requirement 11	0.061	3.791	0.053	17.2296	16.7206	0.5090	0.014
12	STR.12 - Sub-task requirement 12	0.052	2.185	0.142	7.2753	6.2010	1.0743	0.017
13	STR.13 - Sub-task requirement 13	0.054	1.070	0.303	1.1575	0.6810	0.4765	0.008
14	STR.14 - Sub-task requirement 14	0.875	0.029	0.865	0.1600	0.1818	0.0218	0.000
15	STR.15 - Sub-task requirement 15	0.306	2.910	0.089	0.2402	0.4591	0.2189	0.005
16	STR.16 - Sub-task requirement 16	0.407	2.165	0.144	0.3205	0.2548	0.0657	0.019
17	STR.17 - Sub-task requirement 17	0.069	0.2720	0.597	0.5396	0.3263	0.2133	0.001

4.6 Reliability Test

The test-retest reliability technique offers a simple measure of longitudinal reliability. A researcher would expect the results of tests of a group of measurements to remain relatively consistent if same tests are applied to the same group of measurements over time. A necessary condition is that the group of measurements is not altered by confounders during the relevant time interval.

In this study, the researcher obtained measurements from five different columns for each of the projects involved. The test–retest reliability technique was applied on data from the first five projects to check reliability of the instrument [Inspection Checklist (direct measurement)] over time. One group of events (n =3) were tested at the beginning of each STR and another group of events (n = 2) were tested the following day. Such an approach was necessary as duration of the tasks in focus often took two days to complete. The results of the tests were expected to be broadly consistent.

The researcher then used Spearman's rho test to analyse the measurements for consistency. The researcher generated test-retest reliability data through the application of a statistical test (Spearman's rho) to the data so that a coefficient of correlation could be established (Allen & Bennett, 2012). Such an approach is a conventional means of expressing reliability degree, and provides an indication of the probability that first testing and subsequent testing of the same subjects with the same instrument will result in similar scores (Allen & Bennett, 2012).

Spearman's rho Test is calculated using the following equation:

$$\rho = 1 - \frac{6 \sum_i \Delta\mu_i^2}{n\,(n^2 - 1)} \qquad (4.1)$$

Where,
ρ: Spearman's rho
$\Delta\mu$: difference between the mean values for test–retest measurements Δ mean [$\mu_{test} - \mu_{re\text{-}test}$]
$i = 1, 2, 3, \ldots, n$
n: number of STRs

The researcher generated a test-retest calculation of the reliability coefficient of the STRs by applying a Spearman's rho calculation. The researcher used the initial and re-test responses determined for five measurements for each STR in each project to generate the rank correlation. The correlation coefficients derived from the data-set were found to range from between 85.58 and 99.75% (as shown in the following table, Table 4.6).

Table 4.6 Reliability test re-test

STRs	Project 1		Project 2		Project 3		Project 4		Project 5	
	Δμ	Δμ^2	Δμ	Δμ^2	Δμ	Δμ^2	Δμ	Δμ^2	Δμ	Δμ^2
STR.1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
STR.2	-0.010	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.003	0.000
STR.3	10.800	116.64	5.200	27.040	-0.770	0.593	-0.300	0.090	0.700	0.490
STR.4	0.000	0.000	0.000	0.000	0.015	0.000	-0.003	0.000	-0.015	0.000
STR.5	-0.167	0.028	-0.333	0.111	0.000	0.000	0.000	0.000	0.250	0.063
STR.6	-0.167	0.028	-0.167	0.028	0.083	0.007	0.000	0.000	-0.083	0.007
STR.7	-0.400	0.160	-0.830	0.689	0.000	0.000	-0.580	0.336	-0.170	0.029
STR.8	-0.170	0.029	0.330	0.109	0.170	0.029	-0.200	0.040	-0.580	0.336
STR.9	0.133	0.018	0.167	0.028	0.300	0.090	-0.133	0.018	-0.033	0.001
STR.10	0.330	0.109	0.000	0.000	0.000	0.000	0.670	0.449	0.830	0.689
STR.11	-0.330	0.109	0.250	0.063	0.083	0.007	1.000	1.000	-1.080	1.166
STR.12	-0.080	0.006	-1.000	1.000	-0.830	0.689	0.330	0.109	-0.333	0.111
STR.13	0.510	0.260	0.330	0.109	-0.500	0.250	-0.500	0.250	-0.330	0.109
STR.14	0.250	0.063	-0.167	0.028	0.000	0.000	0.167	0.028	-0.083	0.007
STR.15	-0.030	0.001	0.500	0.250	-0.420	0.176	0.670	0.449	-0.170	0.029
STR.16	-0.033	0.001	0.033	0.001	-0.100	0.010	0.000	0.000	-0.050	0.003
STR.17	0.430	0.185	-0.300	0.090	0.400	0.160	2.320	5.382	0.930	0.865
ΣΔμ^2		117.64		29.54		2.01		8.15		3.90
n		17		17		17		17		17
ρ %		**85.58%**		**96.38%**		**99.75%**		**99.00%**		**99.52%**

These correlation coefficient values suggested a strong relationship between original results obtained with the Inspection Checklist, and re-tested results obtained from the same instrument the following day. The Inspection Checklist was considered reliable and suitable for use.

4.7 Chapter Summary

The chapter outlines the procedure applied to gather data sets using two instruments (inspection checklist measurements and a structured interview/observation schedule). Data screening and additional specific analyses implemented to ensure a statistically acceptable data set are discussed. The two gathered data instruments have been discussed and visually described. The chapter describes the application of tests of normality, outlier values, and missing values. The chapter also explains how one-way (ANOVA) was used to conduct the statistical comparative analysis for these differences and examine the means equality and the reliability of the data set. The test-retest reliability method has been adopted to examine the stability and reliability of an instrument over time. These data sets were found to be appropriate and ready to used in operations described in the following chapters.

CHAPTER 5: Building-Project Sub-Task Requirements (*STRs*): Measuring Susceptibility to Quality-Deviation and Defect

5.1 Introduction

The purpose of this chapter is to provide a method and result of an investigation into the susceptibility of STRs to quality deviation and defect. The chapter seeks to address the status quo of inaccurate evaluation of quality deviations. The chapter specifically aims to measure the susceptibility of on-site STRs to quality deviation and construction defect, and their respective exposure to component failure. The chapter further elaborates on how to achieve the aims of the study data was collected at 27 residential structures in Saudi Arabia, through systematic site inspection of 17 STRs for each structure. The chapter outlines how examination of each sub-task occurred with reference to respective project documentation. The chapter also describes how analyses of respective quality practice was conducted using SPC (C_p and C_{pk}). Importantly, the chapter provides a summary of the results achieved for each STR in terms of its susceptibility to deviation. The chapter discusses the results and finishes with a series of conclusions.

5.2 Methodology

In this study, on-site analysis sought the degree of deviation by calculating the difference between the design specifications and code requirements, versus the actual work (i.e. output dimensions) on-site. Subsequently, the susceptibility of the sub-tasks requirements (STRs) to quality deviations and construction defects, and exposure to component failure is identified through detailed determination and understanding of STR patterns. This work addressed multiple on-site case-studies, targeting 17 specific sub-tasks requirements (STRs) related to typical (concrete structure) compression members. The compression members analysed in detail for this research were archetypical column elements, with data generated through structured site-visits to 27 project locations in the city of Riyadh, Saudi Arabia, December 2013 to April 2014.

The researcher assessed 3030 individual STRs between December 2013 to April 2014. The assessment required the targeting of each sub-task, multiple data sources from project documentations in drawings, specifications, and bills of quantities, building code requirements (Saudi Building Code SBC-305A & B and American Concrete Institute Code ACI-318A & ACI-117), and the inspection checklist of the actual work on the project site(s). Two building codes were considered as it was noted anecdotally that the majority of organisations use the ACI code in lieu of the SBC (which was developed with reference to the ACI code). Table 3.3 lists the 17 STRs selected specifically for this study. The targeted measurements' range of tolerances and the maximum and minimum specification boundaries for each sub-task can be drawn from this data and thus, a future degree of deviation can be measured on-site.

5.2.1 Capability process index

Statistical Process Control (SPC) is a quality management tool that monitors activities to facilitate a feedback-loop towards operational management efficiency (Whyte, 2014). SPC includes two popular techniques to measure the capability of the process, namely: control charts; and, histograms (Montgomery, 2009). This study deems the histogram technique as relevant to assess and measure sample frequency distribution within a specific range that includes the mean, the spread of the data and the lower/upper specification limits.

Previous studies have sought to examine performance levels with the inspection process (Jafari 2013; Yates, 2002). This work seeks similarly to address performance; such that the capability of a process, C_p, is a statistical index that refers to the performance of the process based on pre-set specific requirements and assumes normal distribution of the process output (where the standard deviation is represented by "σ" and the upper and lower specification limits are USL and LSL respectively). It is calculated by using the following equation:

$$\text{Process Capability; } C_p = \frac{\text{USL} - \text{LSL}}{6\sigma} \tag{5.1}$$

Comparison of required tolerances, with specification limits of a process, identifies a level of tolerance. If the value of sigma equals 1.5, the capability process value C_p will be 2, which implies that the process opportunity to exceed a specification limit is: 3.4 defects, *parts-per-million (ppm)*. However, for the process to be assumed as capable, the minimum value of the capability process C_p is ≥ 1 (Montgomery, 2009). The main shortfall in the C_p technique seems to be that it does not take into account the shift of the process centre, thus a more rigorous technique for cases to get more precise results and a C_{pk} index, which is similar to the C_p is adapted here. The difference between the two indices is that C_{pk} indicates the response of the process average to the centre of the specification limits (Montgomery, 2009). If the process mean is represented by "μ", C_{pk} is calculated by using the following equation:

$$\text{Process Capability; } C_{pk} = \min\left[\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right] \tag{5.2}$$

The capability process control technique utilised here to analyse the data set is argued as sensitive to assumptions related to the missing values, outlying cases and, normality of the samples.

5.3 Analysis and Findings

Quality control statistics measure and analyse the proximity of quality practice to project specifications, relative to a natural variability of the process. The smaller the value of a capability process index (Table 3.3), the more likely it is for the element (STR1-17 in Table 3.3) to exceed LSL/USLs and fall outside tolerance. Exceeding pre-set design specifications/building codes implies violation of the required tolerance and the output is classified as a defective work:

– The violation of the LSL of STRs often leads to a seriously unsafe component, while the violation of the USL can be classified as an economic issue &/or as a potentially unsafe element depending upon the STR.

Table 5.1 Capability process index

STR	P	Pl	Pu	Cp	Cpl	Cpu	Cpk	PPM < LSL	PPM < USL	PPM Total
STR.1	0.8404	0.1596	0.00	4.2106	0.3320	8.0892	0.3320	129032.29	0.00	129032.29
STR.2	0.8636	0.0326	0.1038	0.5174	0.6147	0.4200	0.4200	50420.17	92436.97	142857.14
STR.3	0.1881	0.2041	0.6079	0.0922	0.2757	-0.0913	-0.0913	193277.31	605042.00	798319.33
STR.4	0.6394	N/A	0.3591	0.5563	0.9923	0.1203	0.1203	0.00	500000.00	500000.00
STR.5	0.9573	0.0399	0.0028	0.7536	0.5839	0.9232	0.5839	26315.79	0.00	26315.79
STR.6	0.9981	0.0008	0.0010	1.0362	1.0465	1.0258	1.0258	0.00	0.00	0.00
STR.7	0.5561	0.0306	0.4133	0.3486	0.6242	0.0730	0.0730	20242.91	380566.80	400809.72
STR.8	0.6379	0.0815	0.2806	0.3293	0.4650	0.1937	0.1937	71428.57	275510.20	346938.78
STR.9	0.9827	0.0173	0.0001	1.0407	0.7042	1.3771	0.7042	0.00	0.00	0.00
STR.10	0.7412	0.0069	0.2519	0.5218	0.8208	0.2228	0.2228	11278.20	199248.12	210526.32
STR.11	0.9241	0.0000	0.0759	1.2873	2.0968	0.4778	0.4778	0.00	68965.56	68965.56
STR.12	0.1299	0.0100	0.8601	0.2077	0.7756	-0.3603	-0.3603	0.00	784000.00	784000.00
STR.13	0.3504	0.1987	0.4509	0.1616	0.2821	0.0412	0.0412	114503.82	366412.21	480916.03
STR.14	0.7741	0.0532	0.1728	0.4263	0.5382	0.3144	0.3144	41666.67	125000.00	166666.67
STR.15	0.7331	0.0863	0.1806	0.3795	0.4546	0.3043	0.3043	74626.87	194029.85	268656.72
STR.16	0.8084	N/A	0.1903	0.6464	1.0005	0.2923	0.2923	0.00	182608.70	182608.70
STR.17	0.8892	0.0406	0.0702	0.5363	0.5813	0.4913	0.4913	41152.26	78189.30	119341.56

5.3.1 STR.1: Steel cross-section area (A_{st})

The acceptable range of the tolerance to meet the pre-set requirement or specifications is between 0.01-0.08 times the gross area A_g of the concrete section (Table 3.3). Table 5.1 shows that the probability P of the samples being within the specification limits nearly equals 84.04%, while 15.96% (P_l: 15.96% - P_u: 0.00%) fall out of the specifications limits (Figure 5.1).

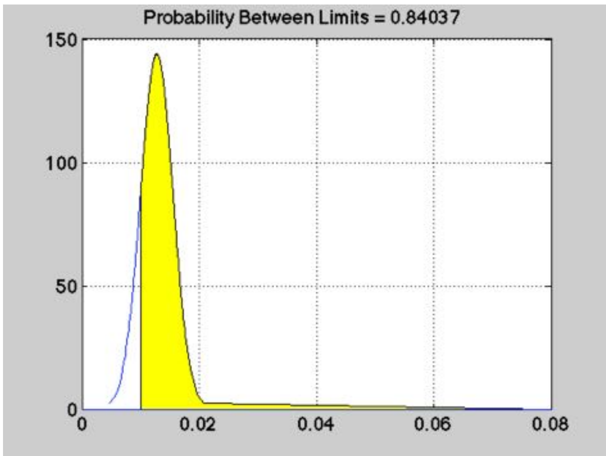


Figure 5.1 Steel cross-section area (A_{st})

Based on the measured values of the capability process indices as provided in Table 5.1, it can be found that the C_p = 4.2106 >> 1 (C_{pl}: 0.3320 - C_{pu}: 8.0892), which indicates that the specification spread is 4.2106 times greater than the 6-sigma σ spread in the process. The value of C_p indicates that the capability process of the variability of STR.1 is tighter than the specification limits, with a very low chance of exceeding the minimal capability. On the other hand, the value of C_{pk} = 0.3320 << 1, causes the mean μ of the capability process index to skew to the left side (μ = 0.0128). This implies an industrial design practice of designing the steel cross-section area A_{st} of longitudinal bars to be closer to the lower specification limit to cut costs in terms of the steel quantity. This causes roughly 15.96% of the samples violating the minimum specification limit. The results suggest that there are approximately 129032.29 parts per million (ppm) non-conforming and that the process is not capable.

– Two improper actions were identified: reducing or increasing either the number of longitudinal bars or the bar diameter ϕ. Therefore, an improvement action, especially for the lower specification limit in this case is required to reduce the variability of the STR.1 to attract the μ of the capability process index into the target.

5.3.2 STR.2: Longitudinal Bars Length

The acceptable range of tolerance for STR.2 to meet the pre-set requirement/specifications is between ±50mm of the designed length of the bar (Table 3.3). Table 5.1 shows that the probability *P* of the samples are within the specification limits, nearly equaling 86.36%; whist 13.64% of the samples (P_l: 3.26% - P_u: 10.38%) fall out of the specifications limits (Figure 5.2).

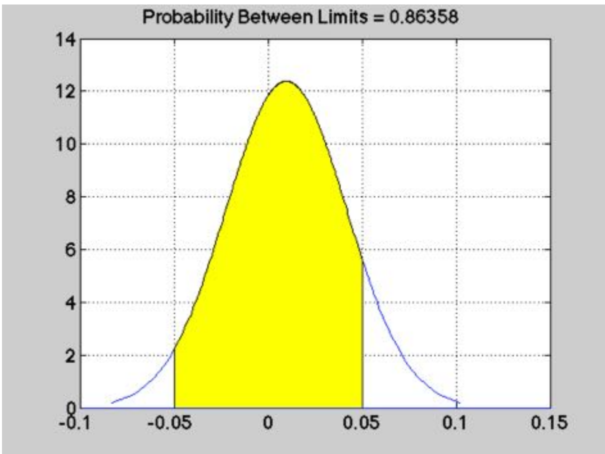


Figure 5.2 Longitudinal Bars Length

Based on the values of the capability process index in Table 5.1, it is found that C_p = 0.5174 < 1 (C_{pl}: 0.6147 - C_{pu}: 0.4200), which indicates that the specification spread is 0.5174 times less than the 6-sigma σ spread in the process. The lower value of C_p implies that the capability process of the variability of STR.1 is broader than the specification limits and possesses a high chance of exceeding the minimum and maximum capabilities. Here, the value of C_{pk} = 0.4200 << 1 and the mean μ of the capability process index is skewed to the right side (μ = 0.0128) (as shown in Figure 5.2).

- Poor workmanship during the actual execution of on-site activity often causes the mean μ of the capability process index to shift from the centre. This suggests that roughly 13.64% of the samples violate both the minimum and the maximum specification limits. The results suggest that there are approximately 142857.14

parts per million (ppm) non-conforming and that the process is not capable. Therefore, to counter this error, an improvement action is required for the upper and lower specification limit, so that the variability of the STR.2 can be reduced and the mean μ can be attracted into the target zone.

5.3.3 STR.3: Lap splices

The acceptable range of tolerance for STR.3 is recommended to be multiplied by 0.83 with allowance of ±25mm, but the lap length cannot be less than 300 mm (Table 3.3) to meet the pre-set requirements. Table 5.1 and Figure 5.3 shows probability *P* of the samples as within specification limits equalling 18.81%, while 81.19% (P_l: 20.41% - P_u: 60.79%) fall out of the specification limits (Figure 1).

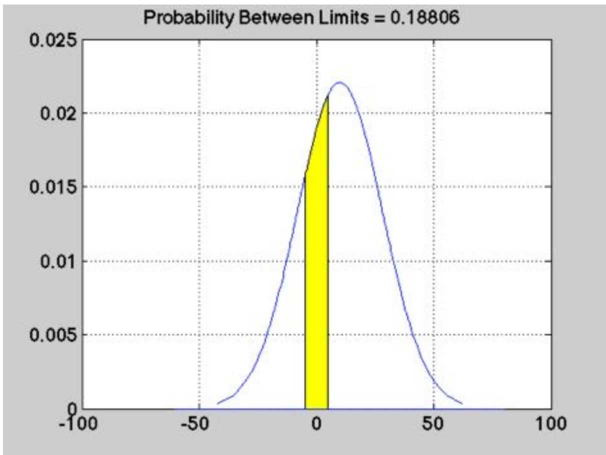


Figure 5.3 Lap splices

Based on the values of the capability process index as measured in Table 5.1, it is found that C_p = 0.0922 << 1 (C_{pl}: 0.2757- C_{pu}: -0.0913), which indicates that the specification spread is 0.0922 times less than the 6-sigma σ spread in the process. The value of C_p reflects that the capability process of the variability of STR.1 is broader than the specification limits and has a high chance of exceeding the minimum and maximum capabilities. Conversely, the value of C_{pk} = -0.0913 << 1, and the mean μ of the capability process index is skewed to the right side (μ = 9.9479) as shown in Figure 5.3.

– This reveals that workers are prone to increasing the length of the lap splice between the longitudinal bars greater than the upper specification limit. This denotes that roughly 81.19% of the samples violated both the minimum and the maximum specification limits. Moreover, it also indicates that there are approximately 798319.33 ppm are non-conforming and reveal that the process is not capable. Therefore, there is a need for an improvement action for the lower and upper specification limits to reduce the variability of the STR.3 and to attract the mean μ of the capability process index into the target.

5.3.4 STR.4: Offset bars - longitudinal bars

The acceptable range of tolerance for STR.4 shall not exceed 1 in 6 (Table 3.3) to meet pre-set requirement or specifications. Table 5.1 shows that the probability *P* of the samples being within the specification limits nearly equals 63.94%, while 35.91% (P_l: N/A - P_u: 35.91%) fall out of the specification limits (Figure 5.4).

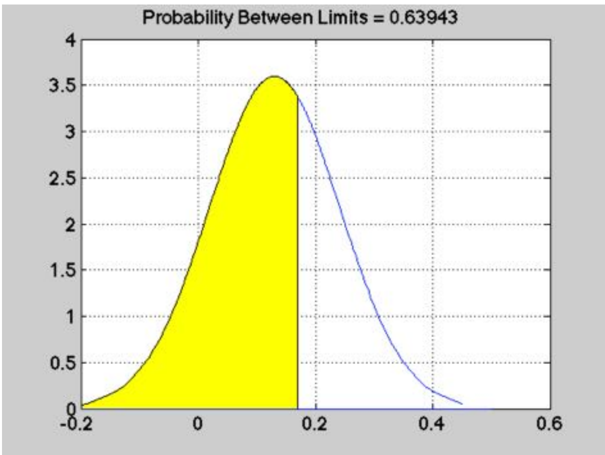


Figure 5.4 Offset bars

Based on the values of the capability process index as provided in Table 5.1, it is found that the C_p = 0.5563 < 1(C_{pl}: 0.9923- C_{pu}: 0.1203), which indicates that the specification spread is 0.5563 times less than the 6-sigma σ spread in the process. The value of C_p implies that the capability process of the variability of STR.4 is broader than the specification limits and with a very high chance of exceeding the maximum capability. Whilst, the value of C_{pk} = 0.1203 << 1, due to that the mean μ of the capability process index is skewed to the right side (μ = 0.1300) as shown in Figure 5.4.

– This means that the workers are usually prone to violate the maximum specification limit. This shows that roughly 35.91% of the samples violated both the minimum and the maximum specification limits. It also shows that there are approximately 500000.00 ppm are non-conforming and reveals that the process is not capable. Improvement action, especially for the upper specification limit, is required to reduce the variability of the STR.4 and to attract the mean μ of the capability process index to target.

5.3.5 STR.5: Ties width

The acceptable range of tolerance for STR.5 is recommended to be less than ±10mm ($D \leq$ 200mm) or ±15mm ($D >$ 200mm) (Table 3.3) as per the pre-set requirement or specifications. Table 5.1 shows that the probability P of the samples being within the specification limits nearly equals 95.73%, while 4.27% (P_l: 3.99% - P_u: 0.28%) fall out of the specification limits (Figure 5.5).

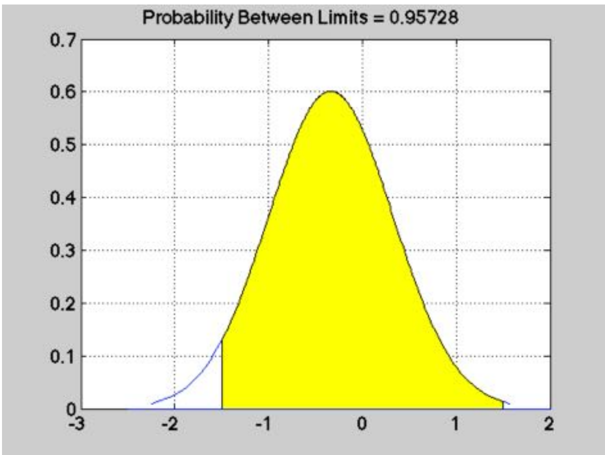


Figure 5.5 Ties width

Based on the value of the capability process index as have been measured in Table 5.1, it can be stated that the C_p value is 0.7536 which is less than 1 (C_{pl}: 0.5839 - C_{pu}: 0.9232), which indicates that the specification spread is 0.7536 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.5 is somewhat broader than the specification limits and with medium chance of exceeding the minimal capability. On the other hand, the value of C_{pk} = 0.5839 << 1, causing the mean μ of the capability process index to be skewed to the left side (μ = -0.3377) as shown in Figure 5.5. The μ value marginally shifted from the center and this may reflect that the susceptibility of the STR pattern to deviation is very low.

– This implies that roughly 4.27% of the samples violated both the minimum and the maximum specification limits. The results suggest that there are approximately 26315.79 parts per million (ppm) non-conforming and that the process is not capable. However, an improvement action for the upper and lower specification limits is still needed to reduce the variability of STR.5 and to attract the mean μ of the capability process index to the target.

5.3.6 STR.6: Ties depth

The acceptable range of tolerance for STR.6 is recommended to be not higher than ±10mm ($d \leq$ 200mm) or ±15mm ($d >$ 200mm) (Table 3.3) to meet the pre-set requirement or specifications. Table 5.1 shows that the probability P of the samples being within the specification limits is nearly 99.81%, while 0.19% (P_l: 0.08% - P_u: 0.10%) fall out of the specification limits (Figure 5.6).

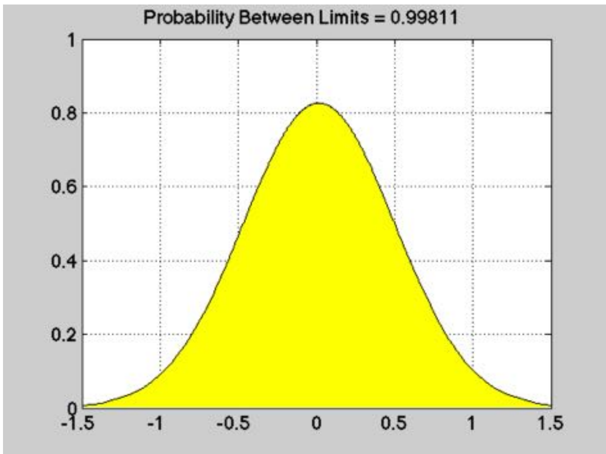


Figure 5.6 Ties depth

Based on the values of the capability process index in Table 5.1, it can be said that the value of C_p = 1.0362 > 1 (C_{pl}: 1.0465 - C_{pu}: 1.0258), which indicates that the specification spread is 1.0362 times greater than the 6-sigma σ spread in the process. The value of C_p implies that the capability process of the variability of STR.6 is tighter than the specification limits and has a low chance of exceeding the maximum and minimum capabilities. Whilst, the value of C_{pk} = 1.0258 > 1 and the very close values of C_p and C_{pk} indicate that the capability process index is centred and the value of μ is very low (0.0149) as shown in Figure 5.6.

– This shows that roughly 0.19% of the samples violated both the minimum and the maximum specification limits (i.e. ±10mm or ±15mm). It also indicates that there are roughly 0.00 ppm are non-conforming and reveal that the process is incapable. Since the mean μ is only slightly shifted from centre, output work usually hits the target point.

5.3.7 STR.7: Ties: Hooks dimensions

The acceptable range of tolerance for STR.7 is recommended to be (bar $\phi = x$) $x \leq 16\phi$ ($6d_b$ ±15mm) or $x = 20\phi - 25\phi$ ($12d_b$ ±15mm) (Table 3.3) to meet the pre-set requirements or specifications. Table 5.1 shows that probability *P* of samples within spec. limits nearly equals 55.61%, while 44.39% (P_l: 3.06% - P_u: 41.33%) fall out of the specification limits (Figure 5.7).

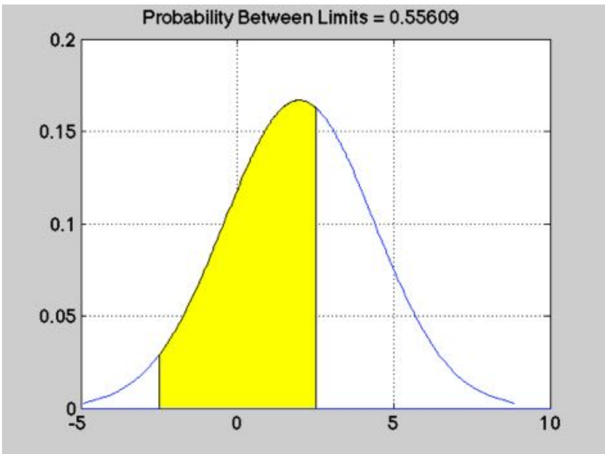


Figure 5.7 Hooks dimensions

Based on the values of the capability process index in Table 5.1, it can be stated that C_p = 0.3486 < 1, (C_{pl}: 0.6242 - C_{pu}: 0.0730), which indicates that the specification spread is 0.3486 times less than the 6-sigma σ spread in the process. The value of C_p shows that the capability process of the variability of STR.7 is broader than the specification limits and with high chance of exceeding the maximum and minimum capabilities. Whilst, the value of C_{pk} = 0.0730 << 1, due to that the mean μ of the capability process index is skewed to the right side (μ = 1.9765) as shown in Figure 5.7.

- This clearly reflects that the workers are more prone to increase the length of the ties hooks. This denotes that roughly 44.39% of the samples violated both the minimum and maximum specification limits. The results suggest that there are approximately 400809.72 ppm non-conforming and that the process is not capable. Therefore, improvement action for both specification limits requires to reduce the variability of STR.7 and attract the mean μ into the target.

5.3.8 STR.8: Ties Angular ^{o}

The acceptable tolerance range for STR.8 is to be (bar $\phi = x$) $x \leq 16\phi$ ($6d_b$ ±15mm) or $x \leq 25\phi$ (90^o or 135^o ±2 ½ degrees) or $x > 25\phi$ (90^o ±2 ½ degrees) (Table 3.3) to meet the pre-set requirements or specifications. Table 5.1 shows that the probability *P* of samples as within specification limits is nearly 63.79%, while 36.21% (P_l: 8.15% - P_u: 28.06%) fall out of the specification limits (Figure 5.8).

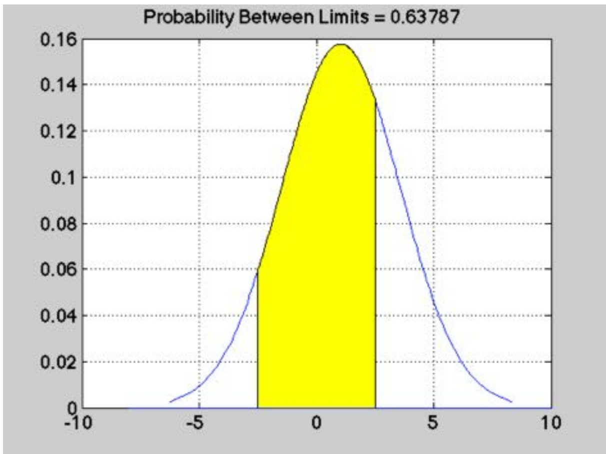


Figure 5.8 Ties Angular ^{o}

Based on the values of the capability process index in Table 5.1, C_p = 0. 3293 < 1 (C_{pl}: 0.4650- C_{pu}: 0.1937), which indicates that the specification spread is 0.3293 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.8 is broader than the specification limits and with very high chance of exceeding the maximum and minimum capability limits. Conversely, the value of C_{pk} = 0.1937 << 1, and the mean μ of the capability process index is skewed to the right side (μ = 1.0297) as shown in Figure 5.8.

– In terms of ties, workers are likely to increase the degree of the hooks ends, thus roughly 36.21% of the samples violated both min. & max. specification limits. In addition, roughly 346938.78 ppm are non-conforming and reveal that the process is not capable. Consequently, counter measures are needed for the lower and upper specification limits to reduce the variability of STR.8 and attract the mean μ into the target.

5.3.9 STR.9: Ties: Bend dimensions

The acceptable tolerance range of STR.9 has to be (bar $\phi = x$) $x \leq 16\phi$ ($4d_b$ ±25mm), x = 16ϕ-25ϕ ($6d_b$ ±25mm), x = 28ϕ-36ϕ ($8d_b$ ±25mm) or $x > 40\phi$ ($10d_b$ ±25mm) (Table 3.3) to meet the pre-set requirements. As per Table 5.1, the probability *P* of the samples being within the spec. limits is nearly 98.27%, while 1.73% (P_l: 1.73% - P_u: 0.01%) fall out of the specification limits (Figure 5.9).

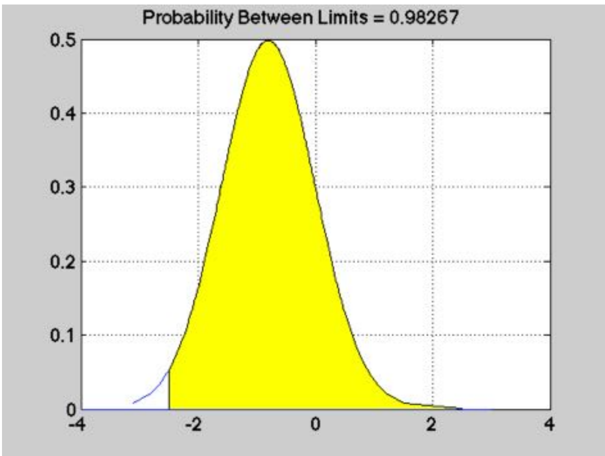


Figure 5.9 Bend dimensions

Based on the values of the capability process index in Table 5.1, C_p = 1.0407 > 1 (C_{pl}: 0.7042 - C_{pu}: 1.3771), which indicates that the specification spread is 1.0407 times greater than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.9 is tighter than the specification limits and has low chances of exceeding the minimal capability. Whilst, the value of C_{pk} = 0.7042 < 1, due to that the mean μ of the capability process index is skewed to the left side (μ = -0.8082) as shown in Figure 5.9. The shift of the mean μ from the centre is somewhat small and this may reflect that the probability of STR.9 to be prone to deviation as very low.

- This denotes that roughly 1.73% of the samples violated both the minimum and the maximum specification limits. The results suggest that there are approximately 0.00 ppm non-conforming and that the process is not capable. Therefore, action remains required for lower spec. limits to reduce variability of STR.9 (re-target mean μ).

5.3.10 STR.10: Horizontal spacing between longitudinal bars

The acceptable tolerance range for STR.10 is minimum $1.5d_b$ and not less than 40mm (Table 3.3) to meet requirements. Table 5.1 shows that the probability *P* of the samples being within specification limits equalling 74.12%, while 25.88% (P_l: 0.69% - P_u: 25.19%) fall outside spec. limits (Figure 5.10).

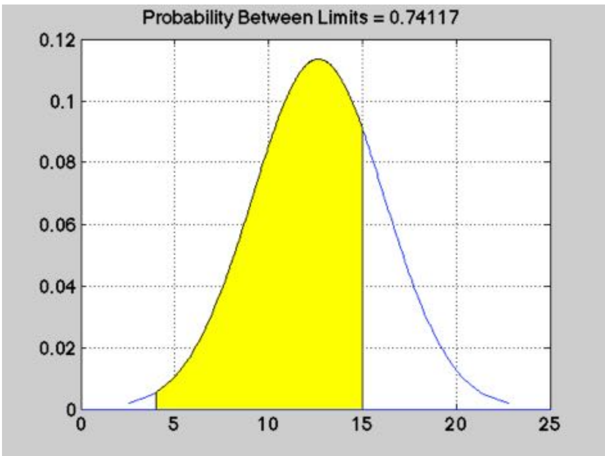


Figure 5.10 Horizontal spacing between longitudinal bars

Based on the values of the capability process index in Table 5.1, $C_p = 0.5218 < 1$ (C_{pl}: 0.8208 - C_{pu}: 0.2228), which indicates that the specification spread is 0.5218 times less than the 6-sigma σ spread in the process. The value of C_p shows that the capability process of the variability of STR.10 is broader than the spec. limits and has a high chance of exceeding min. & max. capability limits; the value of $C_{pk} = 0.2228 << 1$, causes the mean μ to skew to the right (μ = 12.651) as Figure 5.10.

- The majority of the designers are prone to often design the spacing between the longitudinal bars (in project drawings) to be between 100mm to 150mm. This denotes that roughly 25.88% of the samples violated min. & max. specification limits. It also shows that roughly 210526.32 ppm are non-conforming and the process is 'not capable'. Therefore, again improvement action is needed for both the lower and upper specification limits to reduce the variability of STR.10 and attract the mean μ into the target.

5.3.11 STR.11: Vertical spacing between ties

The acceptable range of tolerance for STR.11 provides the maximum limit of 16 longitudinal d_b ($x = 16\ d_b$), 48 tie d_b ($x = 48\ d_b$), or least dimension of the compression member (x = least column width) ±25mm (Table 3.3) as the pre-set requirements. Table 5.1 shows that the probability P of the samples being within the specification limits nearly equals 92.41%, while 7.59% (P_l: 0.0% - P_u: 7.59%) fall out of the specification limits (Figure 5.11).

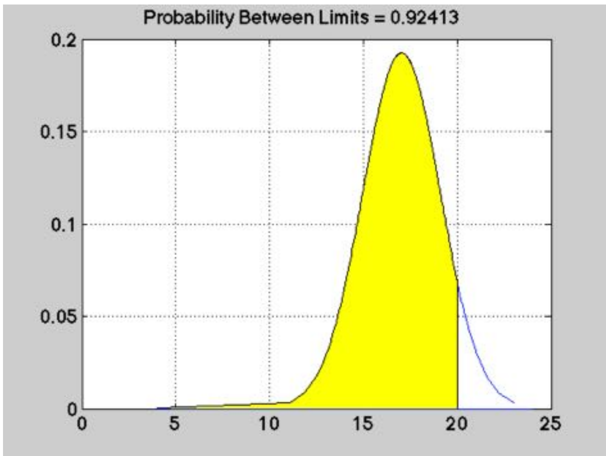


Figure 5.11 Vertical spacing between ties

Based on the values of the capability process index from Table 5.11, it can be found that C_p = 1.2873 > 1 (C_{pl}: 2.0968 - C_{pu}: 0.4778), which indicates that the specification spread is 1.2873 times greater than the 6-sigma σ spread in the process. The value of C_p shows that the capability process of the variability of STR.11 is tighter than the specification limits and with very low chance of exceeding the minimal capability. Whilst, the value of C_{pk} = 0.4778 < 1and the mean μ of the capability process index is skewed to the left side (μ = 17.030) as shown in Figure 5.11.

- The main reason behind this observation suggests that the majority of the designers usually design the vertical spacing between the ties to be 6/m or 5/m, which implies a spacing of 160mm or 200mm respectively. This denotes that roughly 7.59% of the samples have violated both the minimum and the maximum specification limits. Furthermore, roughly 68965.56 ppm are non-conforming and reveal that the process is not capable. Therefore, an improvement action is required especially for the upper specification limit so that the variability of STR.11 can be reduced and the mean μ of the capability process index can be attracted into the target.

5.3.12 STR.12: Spacing above the slab

The acceptable tolerance range for STR.12 is one-half tie spacing above the slab (0.5**x*) ±25mm (Table 3.3) to meet the pre-set requirements or specifications. Table 5.1 shows that the probability *P* of the samples being within the specification limits nearly equals 12.99%, while 87.01% (P_l: 1% - P_u: 86.01%) fall out of the specification limits (Figure 5.12).

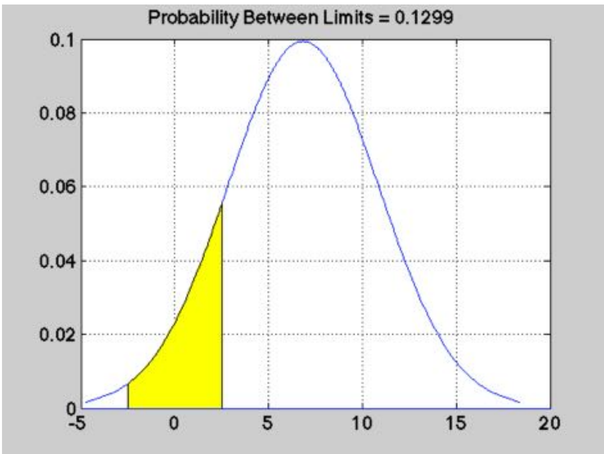


Figure 5.12 Spacing above the slab

Based on the values of the capability process index in Table 5.1, it can be found that the C_p = 0.2077 << 1 (C_{pl}: 0.7756 - C_{pu}: -0.3603), which indicates that the specification spread is 0.2077 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.12 is broader than the specification limits and with very high chance of exceeding the max. & min. capability constrains. Whilst, the value of C_{pk} = -0.3603 << 1, due to that the mean μ of the capability process index skewed to the right side (μ = 6.8371) as shown in Figure 5.12.

- This reflects that the practitioners are usually prone to violating the maximum specification limit. This denotes that roughly 87.01% of the samples violated both the min & max. specification limits. The results suggest that there are approximately 784000.00 ppm non-conforming and that the process is not capable. Therefore, an improvement action must be employed for both upper and lower specification limits so that the variability of STR.12 can be reduced and the mean μ of the capability process be re-targeted.

5.3.13 STR.13: Cross-sectional dimensions: formwork width

The acceptable range of tolerance for STR.13 is; if width $x \leq 30$ cm, +0.9525 cm and -0.635 cm; if width 30 cm < $x \leq 90$ cm, +1.27 cm and -0.9525 cm); or if width $x > 90$ cm, +2.54 cm and -1.90 cm (Table 3.3) to meet the pre-set requirements. Table 5.1 shows that the probability P of the samples within spec. limits nearly equalling P =35.04%, while 64.96% (P_l: 19.87% - P_u: 45.09%) fall out of the specification limits (Figure 5.13).

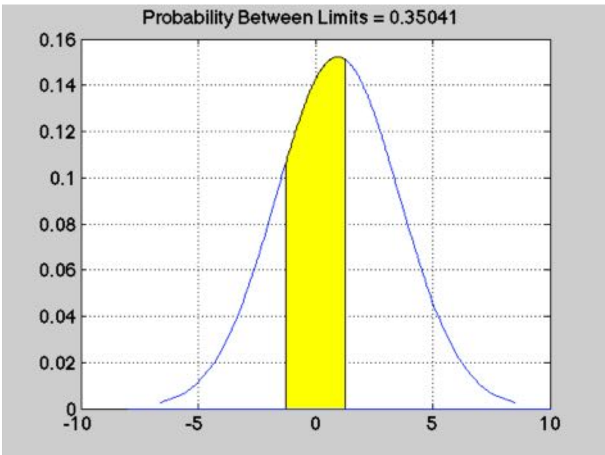


Figure 5.13 Cross-sectional dimensions: formwork width

Based on the values of the capability process index in Table 5.1, it can be found that the C_p = 0.1616 << 1 (C_{pl}: 0.2821 - C_{pu}: 0.0412), which indicates that the specification spread is 0.1616 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.13 is broader than the specification limits and with very high chance of exceeding the maximum and minimum capability constrains. Whilst, the value of C_{pk} = 0.0412 << 1, due to that the mean μ of the capability process index skewed to the right side (μ = 0.9466) (Figure 5.13).

– This reflects the extent to which carpenters, are usually prone to violating the specification limits, especially the maximum limit. This denotes that roughly 64.96% of the samples violated both the minimum and maximum specification limits with roughly 480916.03 ppm as non-conforming, revealing that the process is incapable. Therefore, improvement action needed for lower and upper spec. limits to reduce the variability of STR.13 and to attract the mean μ of the capability process index into the target.

5.3.14 STR.14: Cross-sectional dimensions: formwork depth

The acceptable range of tolerance for STR.14 is recommended as; if depth $x \leq 30$ cm, +0.9525 cm and -0.635 cm; if depth 30 cm < $x \leq 90$ cm, +1.27 cm and -0.9525 cm; or if depth $x > 90$ cm, +2.54 cm and -1.90 cm (Table 3.3) to meet the pre-set requirement or specifications. Table 5.1 shows that the probability *P* of the samples being within the specification limits nearly equals P =77.41%, while 22.59% (P_l: 5.32% - P_u: 17.28%) fall out of the specification limits (Figure 5.14).

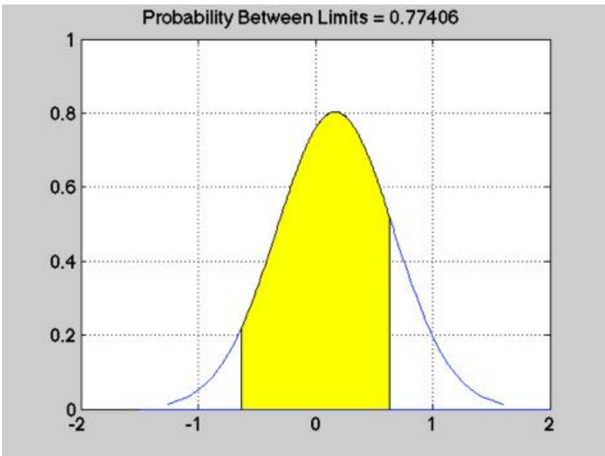


Figure 5.14 Cross-sectional dimensions: formwork depth

Based on the values of the capability process index (Table 5.1), it can be found that the $C_p = 0.4263 < 1$ (C_{pl}: 0.5382 - C_{pu}: 0.3144), which indicates that the specification spread is 0.4263 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.14 is broader than the specification limits and has high chance of exceeding the maximum and minimum capability constrains. Whilst, the value of $C_{pk} = 0.3144 << 1$, due to that the mean μ of the capability process index is skewed to the right side (μ = 0.1667) as shown in Figure 5.14.

- This reflects that carpenters are likely to violate the specification limits, especially the maximum limit. This denotes that roughly 22.59% of the samples violated both the minimum and maximum specification limits. he results suggest that there are approximately 170k- ppm (166666.67 ppm) are non-conforming and reveal that the process is not capable. Again improvement action should be adapted for both upper and lower specification limits so that the variability of

STR.14 can be reduced and the mean μ of the capability process index can be attracted into the target.

5.3.15 STR.15: Concrete cover

The acceptable tolerance range for STR.15 is $d \leq 200$mm, $x = 40$mm (±10mm) or $d >$ 200mm, $x = 40$mm (±15mm); but not less than 1/3 of the cover (Table 3.3) to meet the pre-set requirements or specifications. Table 5.1 shows a probability *P* of samples within the specification limits as 73.31%, while 26.69% (P_l: 8.63% - P_u: 18.06%) fall out of the specification limits (Figure 5.15).

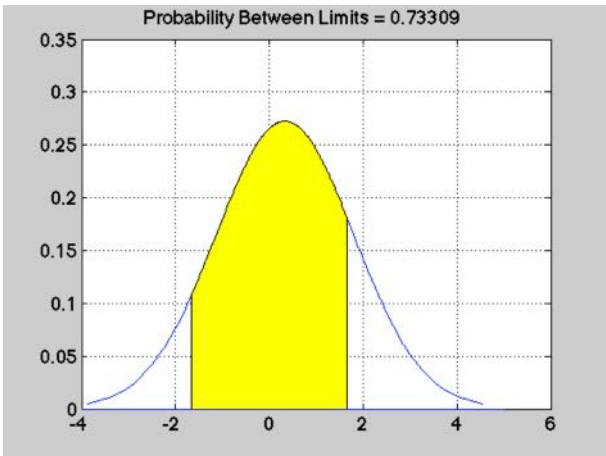


Figure 5.15 Concrete cover

Based on the values of the capability process index as have been measured in Table 5.1, it can be said that the $C_p = 0.3795 < 1$ (C_{pl}: 0.4546 - C_{pu}: 0.3043), which indicates that the specification spread is 0.3795 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.15 is broader than the specification limits and with very high chance of exceeding the maximum and minimum capabilities. Whilst, the value of C_{pk} = 0.3043 << 1, due to that the mean μ of the capability process index is skewed to the right side (μ = 0.3300) as shown in Figure 5.15. Even though the mean μ is only slightly shifted from the centre, the STR pattern is still somewhat highly prone to deviation from sides.

– This denotes that roughly 26.69% of samples violate min. & max. specification limits. Furthermore, it shows that roughly 268656.72 ppm are non-conforming and reveal that the process is again not capable, necessitating improvement action for lower and upper spec. limits, to reduce the variability of STR.15 and re-target the mean μ.

5.3.16 STR.16: Deviation from plumb for column: Column levelling

The acceptable range of tolerance for STR.16 for the top of foundation for height of 26m is 0.3% of the height until a maximum dimension of +2.5cm (26m and less, x = 0.3% of high until maximum +2.5 cm) (Table 3.3) to meet the pre-set requirements or specifications. Table 5.1 shows that the probability P of the samples being within the specification limits nearly equals 80.84%, while 19.03% (P_l: N/A - P_u: 19.03%) fall out of the specification limits (Figure 5.16).

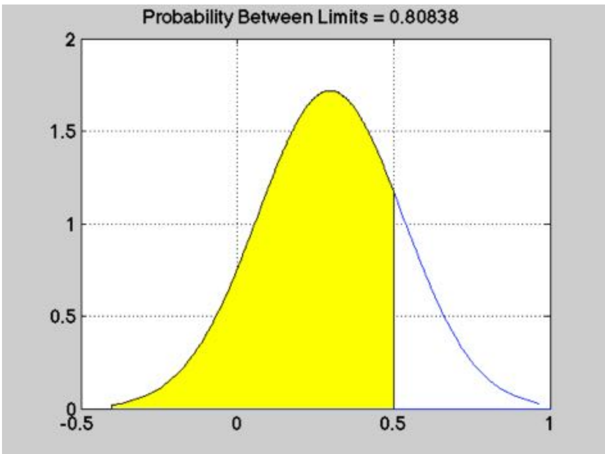


Figure 5.16 Deviation from plumb for column

Based on the values of the capability process index from Table 5.1, it can be stated that the value of C_p is 0.6464, which is less than 1, (C_{pl}: 1.0005 - C_{pu}: 0.2923), which indicates that the specification spread is 0.6464 times less than the 6-sigma σ spread in the process. The value of C_p refers that the capability process of the variability of STR.16 is broader than specif. limits with a very high chance of exceeding the max. capability. Whereas, the value of C_{pk} = 0.2923 << 1, causing the mean μ of the capability process index to be skewed to the right side (μ = 0.2965) (as Figure 5.16).

- Even thought, the mean μ is marginally shifted from the centre, the chance of STR pattern to be prone to deviation is somewhat high from the upper side. This denotes that roughly 19.03% of the samples violated the maximum specification limits. In addition, roughly 182608.70 ppm are non-conforming suggesting a 'non-capable' process. Improvement action is again needed, especially for one-side (upper spec. limit), to reduce the variability of STR.16 and attract the mean μ of the capability process index on-target.

5.3.17 STR.17: Deviation between horizontal elements - Column

The acceptable range of tolerance for STR.17 is to be equal, for distance greater than 30cm (12 in), $x = \pm 5$cm (Table 3.3) to meet the pre-set expectations. Table 5.1 shows a probability *P* of samples within spec. limits as 88.92%, while 11.08% (P_l: 4.06% - P_u: 7.02%) fall out of spec. (Figure 5.17).

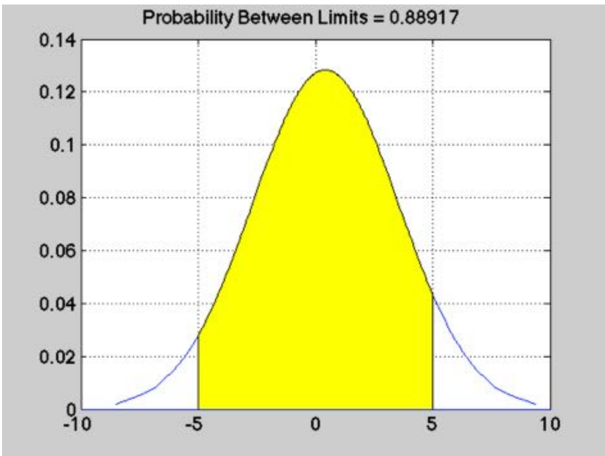


Figure 5.17 Deviation between horizontal elements

Based on the values of the capability process index measured in Table 5.1, C_p = 0.5363 < 1 (C_{pl}: 0.5813 - C_{pu}: 0.4913), which indicates that the specification spread is 0.5363 times less than the 6-sigma σ spread in the process. The value of C_p finds that the capability process of the variability of STR.17 is broader than specification limits, with a very high chance of exceeding the max. & min. capability limits. Whilst, the value of C_{pk} = 0.4913 < 1, due to that the mean μ of the capability process index is skewed to the right side (μ = 0.4193) as is shown in Figure 5.17 above.

– The mean μ is nominally shifted from the centre; likewise, the susceptibility of the STR pattern to deviation is somewhat low. This denotes that roughly 11.08% of the samples violated the maximum specification limits. The results suggest that there are approximately 119341.56 ppm non-conforming and that the process is not capable. Improvement action is recommended for both upper and lower specification limits to reduce the variability of STR.17 and attract the mean μ of the capability process index once more into the target spec.

5.4 External Validity

External validity refers to "knowing whether a study's finding can be generalised beyond the immediate [investigation]" (Voss et al., 2002). External validity is concerned with the extent an experimental effect itself is capable of generalization, and in such cases, to what populations, treatment, settings, or measurement variables is the experimental effect generalisable (Chen, 2010). External validity is a research quality related to the extent to which the results of a study can be generalized from a specific sample to a broader population. Researchers attempt to ensure external validity through selecting a sample size and composition that provides an accurate representation of a given population. Such attempts are necessary as it is rare that the total population is available to the researcher.

The researcher used the statistical process control analyses of the capability of a process C_p and C_{pk} to achieve statistical generalisation in relation to STR deviation. The researcher used a split-half approach to divide the data into two groups with each group retaining 50% of the original data (Bollen, 2014; Drost, 2011; Nunnally, 1978). The split-half method involved the division of the data set based on the chronological sequence of data collection with the first 14 projects constituting the first group and the later 13 projects constituting the second group. Generalisation data was then generated through the application of Mean Magnitude of Relative Error (MMRE) test (Fenton et al., 2008; Foss et al., 2003). Conventionally, the degree of generalisation can be understood through investigating the variation between two similar groups. In this study, the results suggest that the findings can be generalised to situations involving the same conditions and location. The MMRE test is calculated as follows:

Mean Magnitude of Relative Error MMRE:

$$MMRE = \frac{1}{n}\sum_{i=1}^{n} MRE_i \qquad (5.3)$$

Where, *MRE*: Magnitude of Relative Error
n: number of STRs
$i = 1, 2, 3, \ldots, n$

Magnitude of Relative Error MRE:

$$MRE_i = \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{5.4}$$

Where,

y: First group (1st half)

$\hat{y}$: Second group (2nd half)

i = 1, 2, 3, …, n

Table 5.2 MMRE Test for Cp & Cpk

	Cp				Cpk		
	1st half y	**2nd half ŷ**	***MRE$_i$***		**1st half y**	**2nd half ŷ**	***MRE$_i$***
Cp1	3.9514	4.1940	0.06	**Cpk1**	0.3238	0.3405	0.05
Cp2	0.5299	0.5073	0.04	**Cpk2**	0.4522	0.3923	0.13
Cp3	0.0006	0.0006	0.00	**Cpk3**	-0.2207	-0.2399	0.09
Cp4	0.1646	0.1784	0.08	**Cpk4**	-0.4405	-0.4634	0.05
Cp5	0.0175	0.0176	0.01	**Cpk5**	-0.1975	-0.151	0.24
Cp6	0.0379	0.0367	0.03	**Cpk6**	-0.0413	-0.0421	0.02
Cp7	0.0053	0.0049	0.08	**Cpk7**	-0.3048	-0.2315	0.24
Cp8	0.0077	0.0081	0.05	**Cpk8**	-0.1327	-0.1278	0.04
Cp9	0.0135	0.0147	0.09	**Cpk9**	-0.4022	-0.3983	0.01
Cp10	0.0049	0.0052	0.06	**Cpk10**	-1.3666	-1.1777	0.14
Cp11	0.0055	0.0059	0.07	**Cpk11**	-2.6965	-2.8074	0.04
Cp12	0.0044	0.0042	0.05	**Cpk12**	-0.6943	-0.6694	0.04
Cp13	0.0055	0.0058	0.05	**Cpk13**	-0.1021	-0.092	0.10
Cp14	0.0282	0.0275	0.02	**Cpk14**	-0.1049	-0.1042	0.01
Cp15	0.0111	0.0118	0.06	**Cpk15**	-0.0939	-0.0959	0.02
Cp16	0.0543	0.0496	0.09	**Cpk16**	-0.3441	-0.2814	0.18
Cp17	0.0057	0.0058	0.02	**Cpk17**	-0.0533	-0.059	0.11
	Σ MRE$_i$		**0.8675**		***Σ MRE$_i$***		**1.4962**
	n		**17**		***n***		**17**
	MMRE		**0.0510**		***MMRE***		**0.0880**
	MMRE %		**5.10 %**		***MMRE %***		**8.80 %**

The previous table, Table 5.2 shows the degree of variation between the first and second group indicated by C_p and MMRE was 5.10% while C_{pk} was 8.80%. The upshot is the presence of error less than 10% for C_p and C_{pk}, which is acceptable with respect to the generalization of empirical research results. The similarity between the two groups for C_p was 94.90% (100% - 5.10% = 94.90%). C_{pk} was 91.20%. Values of 91.20% and greater indicate theoretically that more than 90% of residential projects in Saudi Arabia demonstrate the same quality practices for the 17 STRs. These results are discussed in the following section.

5.5 Discussion

This study finds that there are significant variations in susceptibility to quality deviation of building sub-task requirements (STRs); in other words different STRs within an overarching task have different susceptibilities to construction defect as a result of their respective on-site installations. It is argued that each STR must be taken into account explicitly in any detailed analyses of (quality deviation in) overarching site-tasks, since STRs with more sensitivity to stray from requisite specifications, have a direct relationship to potential exposure to a building element's failure.

Focus must be placed upon STRs to ensure task, element or component quality compliance. Findings above reveal that previous literature's (Forcada et al., 2013; Mills et al., 2009) concentration upon (and lack of consensus about) failure as a function of the ratio of all construction activities (&/or ratio of constituent elements) may stem from a lack of awareness of the (measurable) importance of sub-task (STR) sensitivity towards quality deviation.

In the findings above (*based upon 3,030 actual STR on-site measurements*), supply of cross-section area steel (STR.1), rebar tie depth (STR.6), rebar tie bend dimensions (STR.9) and vertical cage spacing (STR.11) were noted as *least prone to deviation*, thus requiring less attention by site-manager reps when seeking compliant components. Conversely a site-manager might be justified in requesting that foremen keep a watch upon sub-tasks that typically exceed specification limits such as: rebar lap splices (STR.3), rebar tie hook dimensions (STR.7 & STR.8): cage spacing above slabs (STR.12); formwork cross-sections & coverage (STR.13, STR.14 & STR.15).

Indeed site-managers, in their quest for compliant components, would be justified in closely monitoring several sub-activities with a high susceptibility to deviation, namely: bar lengths and offsets (STR.2 & STR.4); rebar tie widths (STR.5); cage horizontal spacing (STR.10); and, formwork levelling and column positioning deviations from plumb (STR.16 & STR.17).

It is noted that sub-task complexity characteristics (rigorous spec. tolerances) influence potential quality deviations and construction defects. For example, tolerances of cross-sectional dimensions of a column (STR.13 & STR.14) are very constricted, resulting in higher chance of deviation, necessitating close site monitoring. Size/magnitude also pose issues; for example, deviation from plumb of columns (STR.16) reflect the size of the column. In the 27 site locations studied here the larger the size of column, the greater the susceptibility to quality deviations and future defect.

The complex relationship between two or more STRs also impacts upon quality practices; the relationship between concrete cover (STR.15) and the width of tie dimensions (STR.5) and the width of cross-sectional dimensions for formwork (STR.13) are linked. If one or both STR.5 and STR.13 exceed or nearly exceed required tolerances, the probability of STR.15 to exceed tolerance also increases and thus is more vulnerable to quality deviations and defect. Case-study on-site analyses notes humanistic (worker/supervisor) installation degrees-of-error as a variable of: training received; experience in years; experience of location(s); charge-hand supervision; and, inclement site conditions; the correlation between worker competence and STR susceptibility to error (in these case-studies) shall be discussed in detail under separate (future) cover.

Findings show that there is *no* benefit to be gained in conducting uniform inspection procedures (the same inspection effort) across all STRs. Site inspectors can be advised explicitly of comparatively lower or higher susceptibilities (potential respective exposure) to defect. For example, C_p values for tie depth (STR.6) can be expected to hit target, while C_p values for rebar lap splicing (STR.3) generally violate specifications. Resultantly to achieve the desired quality control for columns, an inspector would allocate more attention and effort to rebar splicing, without need to be present at tie depth preparations.

This study provides insight into the construction elements and task activities in terms of their sub-task sensitivities to spec. deviations and defect, although it is recognised that in a minority of cases inspection remains vital even if a C_p value is high (such as confirmation of steel cross-section-areas, STR.1), and that other parameters must be factored-in including degree of risk severity related to key sub-tasks' position on a critical-path, high supply-cost or involved work-method.

Whilst the manufacturing industry is well suited to using Statistical Capability Processes (SPC measurements of C_p and C_{pk}) in order to test quality practices on a factory-floor production line of repetitive automated techniques, it is argued that the less repetitive processes in the construction industry can also benefit from SPCs. Appropriate quantification and analysis of typical on-site sub-task factors in terms of quality deviation and susceptibility to defect can help to draw the big picture and assist in prioritising the attention demand of STRs during the inspection process.

5.6 Conclusion

The comparative vulnerability of sub-tasks to quality deviations and defects on-site, influence a built element's overall potential to violate design specifications and code requirements. The susceptibility of sub task requirements (STRs) to quality deviation and construction defect was explored for 17 STRs for a typical column member, at 27 new residential-building locations, accumulating over 3,000 STR on-site measurements. On-site quality practices were assessed against SBC and ACI design specifications, through the statistical process control indices C_p and C_{pk}.

A need exists for each building-site task to be broken down into sub-tasks to assess requirements towards accurately analysing the potential for quality deviation and construction defect. The susceptibility of STRs within any specific task varies with respective complexity. The majority of SRTs showed low C_{pk} values due to central deviation from pre-set specification targets.

The capability process index technique was applied to the data set generated, and finding that: 23.5% of sub-task requirements, STRs [*supply of cross-section area steel (STR.1), rebar tie depth (STR.6), rebar tie bend dimensions (STR.9) and vertical cage spacing (STR.11)*] showed low susceptibility to deviation from project design documents, whilst 41% of STRs were more likely to exceed the design specification limits [*namely, rebar lap splices (STR.3), rebar tie hook dimensions (STR.7 & STR.8): cage spacing above slabs (STR.12); formwork cross-sections & coverage (STR.13& STR.14& STR.15)*], while the remaining 35.3% of STRs [*bar lengths and offsets (STR.2 & STR.4); rebar tie widths (STR.5); cage horizontal spacing (STR.10); and, formwork levelling and column positioning deviations from plumb (STR.16 & STR.17)*] showed high levels of susceptibility to deviation from the requisite contract specifications. The findings provide a way forward for more effective, targeted inspection to achieve compliance.

Task characteristics dictate the susceptibility of each STR to quality deviations, with complexity (*technical application/ appreciation of design codes*), size and constraining tolerance limits affecting the chances of quality non-conformances (such that column dimension STRs that have tighter constraining limits have a higher chance of deviation for target specifications). The inter-relationships between different STRs influence quality practices and cause some sub-tasks to have higher risk severity.

These observations confirm that on-site inspection cannot be employed equally (nor uniformly) across all STRs; the complexity of STRs inter-relationships, the level of understanding of the pre-set requirements and, offsets from respective tolerance limits that take into account C_p values, must be factored into on-site inspection to achieve (a more efficient inspection programme and) optimum levels of quality control and component conformance.

CHAPTER 6: Task-Based Defect Management: Anatomical Classification

6.1 Introduction

The purpose of this chapter provides the method and result of an investigation into the sensitivity of each STR towards six proposed classes of deviation. The classes were differentiated by whether they represented perfect, acceptable, defective work in relation to acceptable tolerance and the sources of deviation whether design phase, execution phase or both. Chi-square statistical analysis was used to determine the association between the six classes of deviation and each STR. Odds ratio tests were applied to rank the STRs in terms of their proneness to be classified as either: perfect, acceptable, or defective. In total 3030 cases were included in the analysis. The chapter provides the results to each of the mentioned analyses, a discussion of salient findings, and conclusions.

6.2 Background

Defect management is an important activity for project managers in construction. As part of this, defect classification has been seen a necessary step towards improving quality (Davies et al. 1989; Mills et al. 2009). As alluded to above (*section 1.2*) to date, numerous approaches have been applied towards the classification of defects. Each has paid has particular attention to factors relating to construction elements, such as floors, ceilings, or roofs (Forcada et al. 2013; Georgiou, 2010;), location, such as kitchens, bedrooms, or garages, (Forcada et al. 2013), type of defects, such as leaking roofs, cracking, or footings (Georgiou, 2010; Mills et al. 2009), and type of building, such as residential, commercial, or industrial (Mills et al. 2009). While these studies have illuminated the landscape of defect occurrence, they have tended to neglect formal industry benchmarks such as building code regulations, and as a result have arguably produced results with limited generalisability.

Davis et al. (1989) defining quality as "conformance to requirements" argued that deviations could be better managed through measurement. As part of this the authors proposed an "anatomy of deviation." The authors argued that managers needed to ask "which specific tasks were involved in the deviation?" While the team concluded that an objective basis was required for measuring quality, the specific nature of tasks and their sensitivity to deviation was not empirically examined. Since this time the majority of studies of defects have failed to incorporate an objective benchmark from which deviation could be better understood. For instance, Tang et al. (2004) studied deviations related to tasks involved with placing a typical floor. However, the study was based on costs of non-conformance as opposed to frequency and severity of non-conformance with prescribed requirements.

Applying a hierarchical decomposition approach decomposing packages of work (e.g., 1st flour structure), into components (e.g., columns), into tasks (e.g., rebar), into sub-tasks (e.g., longitudinal bars), and then considering the sub-task requirements as prescribed by building codes (e.g., steel cross-section A_{st} : $001A_g \geq A_{st} \leq 0.08A_g$), this study aims to bridge this gap through proposing and testing the application of an anatomical classification approach to defect management based on 17 sub-tasks and their respective building code requirements.

An important aspect of task characteristics is their prescribed requirements. In the construction sector these are provided in project-specific design specifications and building codes, such as Saudi Building Code and the American Concrete Institute Code. The likely strong relationship between task pattern and its sensitivity to quality deviation is the assumption on which this research is based. It is presumed that a more thorough exploration of tasks and their performance in terms of conformance to building code requirements, can lead to accurate characterization of tasks and in particular their respective sensitivities to deviation.

6.3 Research Methodology

It can be restated that this study applied a quantitative approach to calculate sub-task requirement deviation. The severity of deviation was obtained by calculating the difference between design specifications, building code requirements, and the actual dimensions of output work. As mentioned, a data set was developed from data collection at 27 construction project sites in Saudi Arabia between December 2013 and April 2014. By focusing on 17 sub-tasks (Table 1) related to rebar tasks in column element construction, a total of 3030 sub-tasks were investigated. Sub-task drawing, bills of quantities, design specifications and building code requirements (Saudi Building Code SBC-305A&B and American Concrete Institute Code ACI-318A & ACI-117), and an inspection checklist was used.

6.3.1 Classification of the severity of deviation

Six classes of deviation were proposed (Table 2). This classification was based on the extent that the sub-task was prone to be "perfect", "acceptable" or "defective" in relation to acceptable tolerance, as well as the source of any deviation, namely, either the design or execution phase.

Table 6.1 Six classes of deviation

Class 1	Where the design is within the required tolerance and the actual work matches the design, then, there is *no deviation* in the sub-task and the quality output will be considered as *perfect work*.
Class 2	Where the design is within the required tolerance and the actual work does not match the design but is still within tolerance, then, there is *some deviation* in the sub-task and the quality output will be considered as an *acceptable*. In this class, the source of deviation is in the *execution phase* while the design is valid.
Class 3	Where the design is within the required tolerance and the actual work does not match the design and falls out of the required tolerance, then, there is *high deviation with defect* in the sub-task and the quality output will be considered as a *defective*. In this class, the source of deviation is in *execution phase* while design is valid.
Class 4	Where the design is out of the required tolerance and the actual work does not match the design but is still within tolerance, then, there is *some deviation* in the sub-task and the quality output will be considered as an *acceptable*. In this class, the source of deviation is in *design phase* while execution process is valid.
Class 5	Where design and the actual work are out of the required tolerance and the actual work matches the design, then, there is *high deviation with defect* in the sub-task and the quality output will be considered as a *defective*. In this class, the source of deviation is in *design phase* while execution phase is valid.
Class 6	Where design and the actual work are out of the required tolerance and the actual work does not match the design, then, there is *high deviation with defect* in the sub-task and the quality output will be considered as a *defective*. In this class, the source of deviation is in both the *design and execution phases*.

For instance, the design and building code requirements of STR.1, cross-sectional area of rebar steel (A_{st}) for column with A_g as gross concrete cross-sectional area, specifies the ratio between A_{st} and A_g as:

$$0.01A_g \geq A_{st} \leq 0.08A_g$$

The lower ratio limit specifies the minimum rebar steel to resist bending moments and shrinkage or creep issues caused by sustained compression at concrete column. The upper ratio limit, however, avoids placement difficulties due to reinforcement crowding as well as reduces overall budget (Saudi Building Code, 2007). Thus, if the actual project site work longitudinal steel area ratio (A_{st}) was found to be $0.04A_g$ then this would be within the parameters of tolerance and in the absence of design error, be *perfect* (Class - 1).

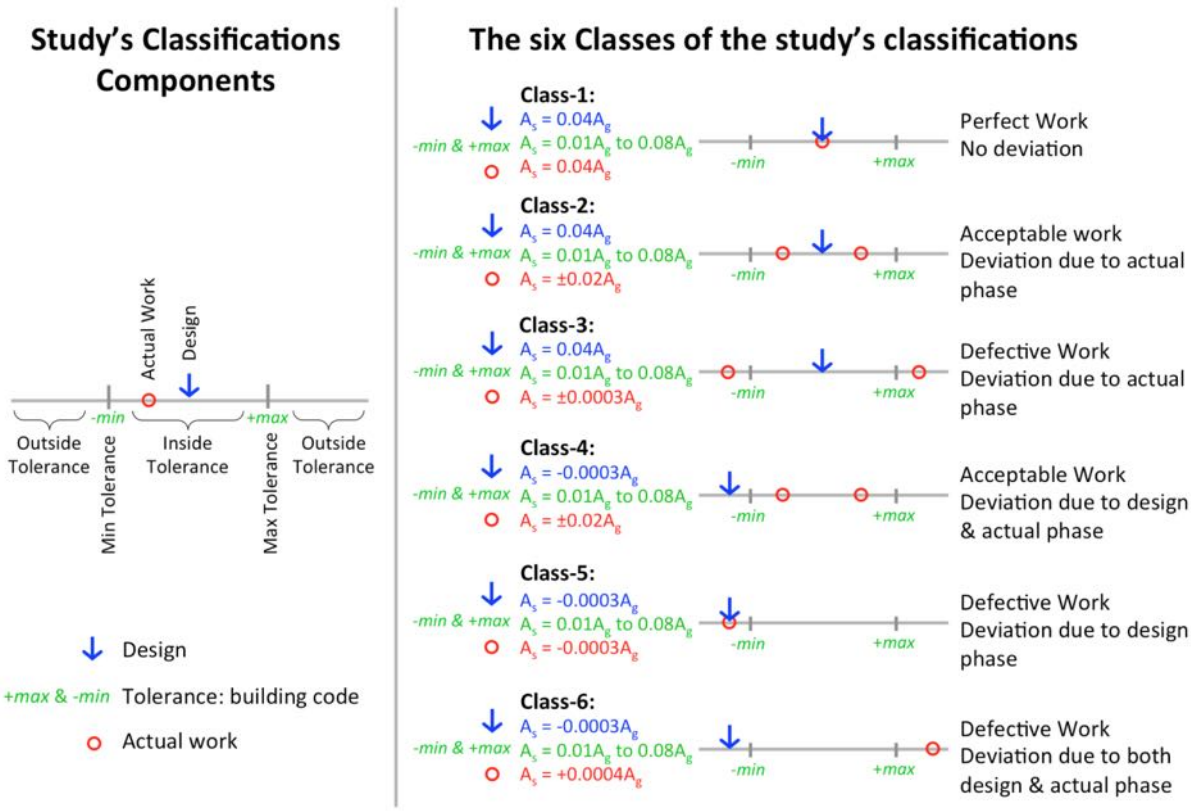


Figure 6.1 Example of STR.1 shown against six classes of deviation

6.3.2 Chi-Square (χ2) test of contingencies and Cramer's V

Statistical examination of variation between categorical or nominal groups is commonly conducted through chi-square analysis. It investigates association between categorical variables (Pallant, 2010). Two assumptions must be satisfied for proper application of a chi-square test. Samples must be randomly drawn from population and the sample size must be large. Maximum 20% contingency cells can have expected values less than 5 (Pallant, 2010). The numbers of degrees of freedom affect chi-square statistical distribution. The chi-square independence test of two variables requires one variable is classified in row and the other in a column to produce a contingency table (row × column). The table tests the relationship between the mutually exclusive categories of column and row variables. The table also shows the frequency distribution between the cells of the table.

The χ^2 statistic is the sum of all $(O-E)^2\ /\ E\ values$ for all $row \times column$ cells.

$$\chi 2 = \sum_i \sum_j \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{6.1}$$

Where

O_{ij} is the observed cell frequency for the $(ij)^{th}$ cell.
E_{ij} is the expected cell frequency for the $(ij)^{th}$ cell.
i is number of columns
j is number of rows

Statistical distribution is governed by the Pearson's χ^2 law having the degree of freedom as (*row*-1) × (*column*-1). The test evaluates association between two categorical variables to determine difference between the observed and expected frequencies in a distribution (Pallant, 2010).

The χ^2 test is significantly influenced by the size of the sample. The value can be overestimated if sample is small and can be underestimated if large. *Cramer's V* test is more suitable in such cases where column and row dimensions are higher than 2 (Allen & Bennett, 2012). Cramer's *V* value can range from 0 to 1. The higher the value of Cramer's *V*, the higher the association between variables (Allen & Bennett, 2012).

6.3.3 Odds Ratio (OR) test

The odds ratio (OR) test is a flexible and robust statistical parameter of how strongly two variables relate. The test quantifies variable relationship strength or effect size as

Pearson correlation coefficient (Bland & Altman, 2000; Davies, Crombie & Tavakoli, 1998). OR is also used to evaluate the ratio between odds of an outcome occurring and it not occurring. It can be considered as the measurement of the ratio between the odds of the presence of a certain quality deviation from a particular task or sub-task and the odds of the absence of that specific quality deviation (Bland & Altman, 2000; Davies, Crombie & Tavakoli, 1998).

Where there are two groups as Group 1 and Group 2 and the probabilities of the events of interest for the two groups are P_1 and P_2 respectively (Bland & Altman, 2000; Davies, Crombie & Tavakoli, 1998), the formula of the odds ratio will be as follows:

$$Odd\ ratio = \frac{P_1/(1-P_1)}{P_2/(1-P_2)} \tag{6.2}$$

6.4 Results

The STRs deviations were examined and the study's classifications were evaluated via 3030 cases. The analysis uses the chi-square test (χ^2) to examine the relationship between the type of the quality deviation and the deviation sources for 17 STRs. Moreover, the odds ratio test was used to rank the sensitivity for all STRs towards perfect-work, acceptable-work and defective-work. The study results list the sub-task deviations from the requirements of the design and tolerance; the deviational condition as either a merely simple deviation or a defective-work; the ratio of each deviational source; and the sensitivity rank of perfect-work, acceptable-work and defective-work for the STR.

6.4.1 Frequency of STRs by class

The occurrence frequency and the ratio of STRs against the six classes of deviation are shown in Table 6.2 It can be noted that some of the STRs were conducted more frequently than others. This was due to the nature of each sub-task. For example, a high number of STR.15 (17.2%) were collected as this sub-task involved measurements on two sides.

Table 6.2 The frequency of STRs by the study classification

		STR 1	STR 2	STR 3	STR 4	STR 5	STR 6	STR 7	STR 8	STR 9	STR 10	STR 11	STR 12	STR 13	STR 14	STR 15	STR 16	STR 17	Total	Ratio %
Frequency of the six cases																				
Case 1	Perfect, No Deviation	20	44	0	14	43	73	5	53	0	7	20	3	27	94	67	35	8	513	16.9
Case 2	Acceptable, Actual Deviation	95	58	23	3	68	61	143	11	134	177	237	24	41	19	330	74	208	1706	56.3
Case 3	Defective, Actual Deviation	6	17	100	51	23	0	120	36	0	36	7	103	63	18	119	21	30	750	24.7
Case 4	Acceptable, Design-Actual Deviation	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	29	1
Case 5	Defective, Design Deviation	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0.1
Case 6	Defective, Design-Actual Deviation	8	0	0	0	0	0	0	0	0	18	0	3	0	0	0	0	0	29	1
Frequency of the expected output work																				
Case 1	Perfect work	20	44	0	14	43	73	5	53	0	7	20	3	27	94	67	35	8	513	16.9
Case 2+4	Acceptable work	95	58	23	3	68	61	143	11	134	206	237	24	41	19	330	74	208	1735	57.3
Case 3+5+6	Defective work	16	17	100	51	23	0	120	36	0	55	7	106	63	18	119	21	30	782	25.7
Frequency of the deviation sources																				
Case 1	No Deviation	20	44	0	14	43	73	5	53	0	7	20	3	27	94	67	35	8	513	16.9
Case 2+3	Actual	101	75	123	54	91	61	263	47	134	213	244	127	104	37	449	95	238	2456	81.1
Case 4+6	Actual & Design	8	0	0	0	0	0	0	0	0	47	0	3	0	0	0	0	0	58	1.90
Case 5	Design	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0.10
	Total	131	119	123	68	134	134	268	100	134	268	264	133	131	131	516	130	246	3030	100
	Ratio %	4.3	3.9	4.1	2.2	4.4	4.4	8.8	3.3	4.4	8.8	8.7	4.3	4.3	4.3	17.2	4.3	8.1	100	100

6.4.2 Relationship between STR and deviation class

The frequency of the six classes is also shown in Table 6.2. As can be seen, Class 2, acceptable deviation in execution phase, was the most common deviation occurrence (56.3%). This was followed by Class 3, unacceptable deviation i.e. defective in execution phase, (24.7%), which had a higher occurrence than Class 1 perfect (16.9%). Class 4, 5, and 6 had very low occurrence at 1.0, 0.1, and 1.0 respectively.

Table 6.3 shows that, one of the χ^2 test assumptions has been violated (50 cells [46.0%] have expected count < 5). In this case, the value of likelihood ratio Cramer's *V* shall be used. The likelihood ratio Cramer's *V* test for independence found within indicates an insignificant association between the classification and STRs. This is based on the Cramer's *V* value of (80, n = 3030) = 0.372, (p< 0.05), which indicates a medium to low association. Therefore, it can be concluded that the general pattern of the study's classification, i.e. six classes, for STRs is a predominantly independent relationship. Having said this, isolated STRs were found to have atypical frequencies of classes and this may suggest a need for higher caution when dealing with these tasks.

Table 6.3 Chi-Square χ^2 Test for relationship between STR and deviation class

	Ratio of the six classes		
	Value	**df**	**Asymp. Sig. (2-sided)**
Pearson Chi-Square	2102.56 [a]	80	0.000
Likelihood Ratio	1835.45	80	0.000
Linear-by-Linear Association	7.398	1	0.007
	Value	**Approx. Sig.**	
Likelihood Ratio Cramer's V	0.372	0.00	
N of Valid Cases	3030		

[a]50 cells (46.0%) have expected count < 5. The minimum expected count is 0.07.

6.4.3 Analysis of the expected output works for all Sub-tasks Requirements

Table 6.2 displays the distribution and the ratio of the frequencies of all the expected deviation degrees by all STRs. This table displays that the acceptable, i.e. classes 2 and 4 constituted over half of the cases (57.3%). The unacceptable deviation i.e.

defective, classes 3, 5 and 6 constituted approximately a quarter of the cases (25.7%). While the perfect, i.e. class 1 was recorded with the lowest ratio (16.9%).

Table 6.4 shows that, the data analysis fulfilled the assumptions of χ^2 test and the outcomes of the χ^2 test that examined the significant difference in the degree of deviation for all STRs indicated that a significant association between the degree of deviation and the STRs; χ^2 (32, n = 3030) = 1601.085, (p< 0.05). The Cramer's V value of V (32, n = 3030) = 0.514, (p< 0.05), indicating a high to medium association suggests a statistically significant association between degree of deviation and STRs. Therefore, it can be concluded that the general pattern of the degree of deviation; i.e. perfect, acceptable or defective; for all STRs is a predominantly dependent relationship. However, some cases might be somewhat deviated and demand higher attention and more caution from the workers on inspectors of these STRs.

Table 6.4 Chi-Square χ^2 Test for the expected output works for all STRs

	Ratio of the expected output work		
	Value	**df**	**Asymp. Sig. (2-sided)**
Pearson Chi-Square	1601.08 [a]	32	0.000
Likelihood Ratio	1567.38	32	0.000
Linear-by-Linear Association	3.934	1	0.047
	Value	**Approx. Sig.**	
Likelihood Ratio Cramer's V	0.514	0.00	
N of Valid Cases	3030		

[a] 0 cells (0.0%) have expected count < 5. The minimum expected count is 11.52.

The frequency of the perfect work is 16.9% (513 cases), which represents the lowest ratio. This implies that the requirements cannot be easily applied accurately as per the design and building code requirements. Some of the STRs; in particular STR.3, STR.9 and STR.12; have zero or low frequencies. This indicates the presence of some complexities related to these STRs that challenge their production as per the design and building code requirements. In contrast, the frequency of acceptable is 57.3% (1735 cases) that represents the highest ratio comparing to the rest criteria. As some of STRs are harder to fabricate precisely as per the specifications (ACI-318, 2008), some degree of deviation is acceptable as long as the outcome of the final product falls within the tolerance. The majority of the STRs have a high frequency of acceptable; however, some of them were noted with very low frequencies such as STR.3 and STR.11. Finally, the frequency of defective equals 25.7% (782 cases) of the total cases. This indicates that the quality practice is poor and almost quarter cases are classified as defective. Only two STRs out of the 17 STRs were recorded with no defects, which are STR.6 and STR.9. The rest of the STRs violated the tolerance of the design and the building code requirements with different degrees of severity and risk.

6.4.4 Analysis of deviation sources by STR

Table 6.2 displays the frequency and ratio of all deviation sources. It displays that the "actual" dominated majority of the cases (81.1%). The class of "no deviation" was recorded as nearly 16.9%. The ratio of "the actual and design" was recorded to be around 1.90%. Finally, the ratio of "the design" was recorded to be only 0.1%.

Table 6.5 shows that, one of the χ^2 test assumptions has been violated (30 cells [41.0%] have expected count < 5). In this case, the value of likelihood ratio Cramer's *V* shall be used. The likelihood ratio Cramer's *V* test for independence found within indicates an insignificant association between the classification and STRs. This is based on the Cramer's *V* value of (48, n = 3030) = 0.368, (p< 0.05), which indicates a medium to low association. Therefore, it can be concluded that the general pattern of the deviation sources for all STRs is predominantly independent relationship.

Table 6.5 Chi-Square χ^2 Test of the deviation sources by STR

	Ratio of the deviation sources		
	Value	**df**	**Asymp. Sig. (2-sided)**
Pearson Chi-Square	1232.76 [a]	48	0.000
Likelihood Ratio	972.59	48	0.000
Linear-by-Linear Association	2.137	1	0.144
	Value	**Approx. Sig.**	
Likelihood Ratio Cramer's V	0.368	0.00	
N of Valid Cases	3030		

[a] 30 cells (41.1%) have expected count < 5. The minimum expected count is 0.07.

The frequency of "the actual source" class equals 2456 cases (81.1%) that represent the highest ratio. The projects quality practices and control during the STRs fabrication process as the major source of quality deviations. However, this does not mean that the outcomes of all STRs have a similar or convergent ratio from this class (i.e. the actual work). In contrast, the frequencies of "the actual and design source" and "the design source" classes equal 58 cases (1.90%) and 3 cases (0.1%) respectively and both represent very low ratios. Two aspects are indicated by this. Firstly, the design errors in these STRs rarely occur. Secondly, some design specifications directly followed the building code requirements and the designers copied the STR from the building code requirements without any changes. For instance, in STR.4 (i.e. bar offset for longitudinal bars), the designers often mentioned the required slop in the drawings as the building code requirements (i.e. the slop 1 of 6) without any change. Contrarily, for STR.10 (i.e. horizontal spacing for cage assembling), the designer often changed the steel quantity of each or a number column as a new sub-task. Thus, the quality of STR.10 is more likely to deviate and 48 cases have been recorded as quality deviation for STR.10. Finally, the frequency of "no deviation" class equals 513 cases (16.9%) that represent the zero deviation source or the cases that were conducted perfectly without any quality deviation.

6.4.5 Sensitivity of STRs towards deviation

This analysis addressed the sensitivity of STRs towards exposure to deviation. The odds ratio test was applied to rank the STRs in terms of their proneness to be classified as perfect, acceptable and defective. STR.17 was taken as the sensitivity benchmark, i.e. STR.17 odds ratio = 1, to compare the STRs. Higher sensitive STRs have odds ratio > 1 while lower sensitive STRs have odds ratio < 1; as compared with STR.17. Table 6.6 displays the sensitivity ranks for STRs for three criteria: perfect-work, acceptable-work and defective-work.

To calculate the odds ratio (OR) for two STRs, for example STR.1 relative to STR.17, the frequencies of event occurrence and nonoccurrence should be determined. Table 6.2 shows that the frequency of the perfect works for STR.1 is 20 cases out of the total 131 cases, while 111 cases represent the rest of the cases; which are acceptable and defective work deviations. Similarly, the frequency of the perfect works for STR.17 is 8 cases, while the remaining 238 (i.e. 246 – 8 = 238) cases are not perfect works deviation. Then the occurrence probability of the perfect works for both STRs is computed. For example, the probability of occurrence of perfect works for STR.1 is 20, and 8 for STR.17; therefore, the ratio of STR.1 relative to STR.17 equals is 2.5 (20/8 = 2.5). Then, the probability of nonoccurrence of perfect works for both STRs is computed. For example, the probability of nonoccurrence of the perfect works is 111 for STR.1, and 238 for STR.17. Therefore; the ratio of STR.1 relative to STR.17 equals 111/238 = 0.4664. Finally, the OR value for STR.1 relative to STR.17 equals 2.5/0.4664 = 5.360.

Table 6.6 shows that the OR value of STR.1 under the perfect-work criteria is 5.360, 95% CI: 2.144–11.87, with STR.17 as benchmark. This means that STR.1 is 5.360 times more likely than STR.17 to achieve perfect-work status, i.e. no quality deviation. Moreover, the sensitivity of STR.1 to be classed as perfect-works has been ranked at the 9th most likely to achieve perfect status overall. Based on the OR value, STR.14 (OR: 75.58, 95% CI: 33.93–168.3) was ranked 1st being found to be the most likely STR to achieve perfect-work status, and 75.58 more times likely than STR.17. In contrast, STR.7 (OR: 0.111, 95% CI: 0.014–0.897) was noted as having the least likelihood to achieve perfect-work status than STR.17 and ranked on the 17th level comparing with the rest of STRs.

Similarly, Table 6.6 shows that with respect to the acceptable-work criterion, the highest sensitivity to exposure to acceptable deviation of the STR.9 is (OR: 24.29, 95% CI: 3.297–179.1) and was ranked 1st. This indicates a more likely exposure of STR.9, 24.29 times, to the acceptable-work deviation than STR.17. In contrast, the least sensitive to exposure to acceptable-work criterion of the STR.4 is (OR: 0.009, 95% CI: 0.003–0.029) and was ranked 17th for this criterion. This means that the likelihood of STR.4 to acceptable works deviation is less, 0.009 times than STR.17.

Finally, Table 6.6 shows that concerning STRs and the defective-work criterion, the most sensitive to exposure to defective-work of the STR.3 is (OR: 30.60, 95% CI: 17.03–54.99) and was ranked 1st level. This means that STR.3 is more likely to exposure to the defective-work deviation, 30.60 times than STR.17. Contrarily, STR.6 is noted as the least sensitive defective works exposure (OR: 0.054, 95% CI: 0.007–0.402) and was ranked 17th level. This means that STR.6 is less likely to the defective works deviation exposure, 0.054 times than STR.17.

Table 6.6 STR sensitivity ranks for three criteria

STRs	Perfect-work				Acceptable-work				Defective-work			
	Odds Ratio	95% Confidence Interval		Sensitivity Rank	Odds Ratio	95% Confidence Interval		Sensitivity Rank	Odds Ratio	95% Confidence Interval		Sensitivity Rank
		Lower	Upper			Lower	Upper			Lower	Upper	
STR.1	5.360	2.144	11.87	9	0.501	0.298	0.842	5	1.002	0.524	1.914	12
STR.2	16.83	7.581	37.37	4	0.180	0.109	0.296	10	1.200	0.633	2.276	10
STR.3	0.238	0.029	1.924	15	0.043	0.024	0.076	13	30.60	17.03	54.99	1
STR.4	8.010	3.195	20.07	7	0.009	0.003	0.029	17	20.75	10.61	40.59	3
STR.5	14.06	6.365	31.04	5	0.188	0.116	0.305	9	0.976	0.511	1.864	14
STR.6	35.60	16.28	77.84	2	0.153	0.094	0.248	11	0.054	0.007	0.402	17
STR.7	0.111	0.014	0.897	17	0.222	0.146	0.338	8	5.838	3.717	9.169	5
STR.8	33.55	14.97	75.15	3	0.023	0.011	0.046	16	4.050	2.316	7.084	6
STR.9	0.224	0.028	1.808	16	24.29	3.297	179.1	1	0.054	0.007	0.402	16
STR.10	0.798	0.285	2.234	13	0.620	0.396	0.971	4	1.817	1.119	2.950	8
STR.11	2.439	1.054	5.644	11	1.604	0.946	2.717	2	0.196	0.084	0.455	15
STR.12	0.703	0.183	2.695	14	0.041	0.024	0.073	14	27.47	15.53	48.59	2
STR.13	7.724	3.395	17.57	8	0.083	0.050	0.138	12	6.671	3.993	11.14	4
STR.14	75.58	33.93	168.3	1	0.031	0.017	0.056	15	1.147	0.613	2.147	11
STR.15	4.439	2.097	9.396	10	0.321	0.218	0.475	6	2.158	1.399	3.329	7
STR.16	10.96	4.905	24.49	6	0.241	0.148	0.394	7	1.387	0.759	2.536	9
STR.17*	1.000	0.369	2.708	12	1.000	0.613	1.631	3	1.000	0.622	1.607	13

* The reference category is: STR.17

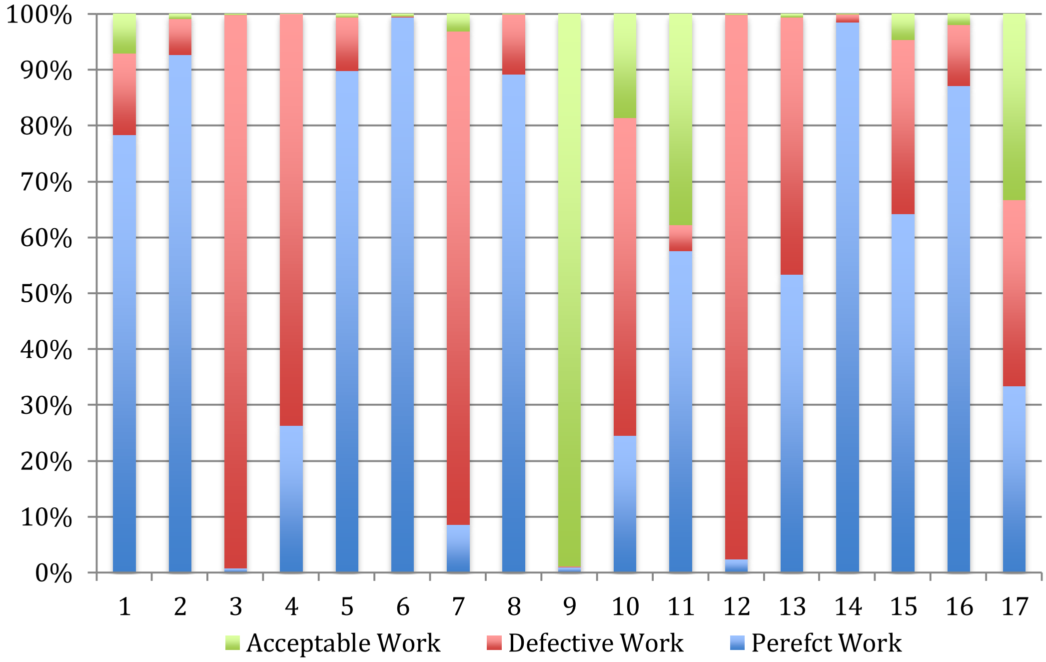


Figure 6.2 Sensitivity towards deviation for all STRs with STR.17 as reference

Figure 6.2 shows that based on the values of the odds ratio; the deviation sensitivity variations of all STRs towards perfect-work, acceptable-work and defective-work is measured with taken STR.17 as benchmark. For the perfect-works criteria, it seems that the majority of STRs are more sensitive than STR.17, especially STR.6 and STR.14. For the acceptable-works criteria, it seems that the majority of STRs have lower sensitivity than STR.17 except STR.9 and STR.11. For the defective-works criteria, majority of STRs are more sensitive than STR.17, especially STR.3 and STR.12. It can be extracted from these results that the nature of each STR differs in terms of its sensitivity to the quality deviations and construction defects. This variation should be considered during the design and the implementation of each STR. An appropriate proactive strategy can be developed from the understanding of this variation to avoid or at least limit the degree of the deviation.

6.5 Discussion

Conventionally, task, sub-task or design specifications are not necessarily implemented as 'perfect' in the construction industry if compliance falls within building code tolerance (Concrete Reinforcing Steel Institute, 1996). Many of STRs variations cannot be noticed during the implementation stage or even the inspection process. However, some of deviations can lead to unsafe structures or at the very least result in future economic knock-on issues. Therefore, some STRs should receive more attention to ensure the STR compliance with the design specifications and building code requirements, especially if they lead to cost and time overruns. Construction industry quality control strategies and practices still suffer from quality process verification difficulties (Jafari & Love, 2013), particularly at the micro level or the STRs. The nature of specific STR can be more complex than the others. Therefore, increase in the complexity may lead to increased tolerance violation probability and higher STR sensitivity towards deviation.

The classification of tasks into small and manageable STRs makes it easier to identify and understand the individual and overall pattern of STRs. Love et al. (2009) stated the decomposition of work or activity package into manageable smaller sub-tasks as a probably easier but a time consuming long procedure. According to Assaf et al. (1995), poor inspection is partly responsible for construction defects as it ignores some important tasks or specifications. However, the nature of STR to be inspected has been given less attention by the researchers. Therefore, the study classification has been applied to remove this uncertainty and reveal the sensitivity degree for those STRs towards the quality deviations. The findings of this study show that the general pattern for the majority of the total 17 STRs is proneness to deviation either as acceptable, 10 STRs; or defective, 4 STRs whereas the tendency to be produced as perfect had a lower ratio, 3 STRs out of 17 STRs. Nonetheless, variation exists in terms of sensitivities towards deviations of STRs. The variation can increase the degree of difficulty in conduction of controlled inspection and uncertainty about which STR needs more attention. It can also increase uncertainty for the prediction process or proactive and preventive actions, especially for STRs often leading to high-risk outputs; such as unsafe and unusable buildings; or leading to high expenditure due to rework or delay.

The sources of deviation have been classified into four criteria. The ratio for each class is also identified. Surprisingly, the study found that the deviation due to the actual process during the fabrication works of STR dominated the majority of the deviated cases, i.e. 81.1% of cases. However, not all of the cases that deviated due to the actual process are considered construction defects as deviations are from the building code requirements. The majority of these cases were classified as merely quality deviations and acceptable. This outcome corresponds to some extent with some previous studies. Jafari and Love (2013) estimated that the construction-related activities, including quality deviations and construction defects, have a non-conformance frequency of about 70% while engineering and procurement-related are 20% and 10% respectively. In contrast, the Building Research Establishment [BRE] (1982) reported that 50% of construction defects arise from the design stage. This variation between the previous studies can be attributed to the degrees of accuracy or level of the STRs investigation. Another surprising result is that only 2% of the deviations were due to two deviation source criteria; 1) both actual and design processes and 2) only design process. The low deviation ratio can be from the direct design of most STRs based on the building code requirements without any changes or deeper understanding of some STRs by designers. These could reduce the STRs sensitivity towards deviation.

Most importantly, this study implies that the deviation pattern of all or even groups of STRs in construction industry cannot be generalized as none of the investigated STRs have same quality deviation sensitivity. This may highlight the need for defect management research to focus at the sub-task requirement level in order to generate meaningful representations of the likelihood of defect occurrence. In other words, analyses of defects which focus on larger conditions such as whole element, location, materials or otherwise may be providing an incomplete and largely unhelpful representation of the likelihood of defects given a particular construction project. It may be noted that many studies thus far concerning defect occurrence in construction provide widely varying results (Cheng, & Li, 2015) Therefore, the study suggests a dynamic strategy or tool that can predict the different types of STRs. Furthermore, it may improve the quality control and inspection performance through the use of available deviation patterns information of each STR. In this study, some limitations have been encountered related to severity of risks of each STR. Therefore, the study recommends that in order to build a comprehensive picture about the deviation degree of each STR, the severity risks of all STRs must be identified.

6.6 Conclusion

Construction practices often contain quality deviations and construction defects that are mostly tolerable if they are within the design and building code tolerance limits. Nonetheless, some deviations can lead to on-going and future risk knock-on work, in terms of cost, time and safety. Further classification of a task into micro level manageable STRs can produce better understanding about the deviation patterns of all the STRs, resulting in appropriate allocation of inspection effort to rectify the deviation occurrence. This study classifies the deviation sources in four criteria based on the study's classification; no deviation, deviation from actual work, deviation from design, and deviation from both design and actual work. 3,030 cases of 17 STRs from elements under compression, i.e. column, of the erected 27 concrete residential building construction projects were studied. The study has also investigated the deviation pattern and the sensitivity to deviation of the STRs. The main findings of this study are:

- Most of the STRs were found to be prone to deviations. 10 of the 17 STRs were observed as acceptable works and 4 STRs as defective works. While only 3 STRs could be classified as perfect works.
- The sensitivities of the STRs towards deviations and defects are varied across all STRs, reducing the control over STRs and increasing the uncertainty about the STR attention requirements. Due to this inability of STR pattern generalisation, severity risks of all STRs must be identified and suitable proactive actions can, therefore, be developed.
- Deviations from the actual fabrication works formed 81.1% of the investigated cases but most of the cases were acceptable deviations from the building code requirements.
- The design phase and the design and actual process produced only 2% of the deviations.

This six-class classification approach contributes to the body of defect-occurrence knowledge by providing a platform for researchers to model future investigations into accurate defect analysis.

CHAPTER 7: Research Framework Using Bayesian Belief Networks Technique

7.1 Introduction

The interaction between the requirements of construction tasks and the causes of quality deviation and defects is somewhat poorly understood. The previous chapters focused on the nature of quality deviation in relation to STRs. In Chapter 5, the measurement of quality deviation in relation to STRs using quality control process was discussed. In Chapter 6, the classification of quality outputs possible/options into perfect work, acceptable with actual work, defective with actual work, acceptable with actual work, defective with actual work and defective with actual work was discussed. The work that the previous two chapters refer is limited to investigating the sensitivity of STRs to quality deviation and defects. In the following chapter, the factors that underpin such sensitivity are investigated.

The principle of association states that the constant concurrence of events will be the result of an underlying assumption (Hume, 2008). In other words, observed events may suggest a causal relationship, which can predict future events. The notion highlights the importance of determining what factors impact upon the sensitivity of STR to quality deviations and defects. Recent research in construction industry has described mathematical models explaining causal relations amongst direct and root causes giving rise to quality deviations, defects or rework. The following chapter introduces a method that applies Bayesian belief networks BBN to quantify causation of quality deviation and defects in construction projects. The method provides means to determine direct factors, such as workers and materials and so on that have most likely influence on quality deviation for each STR. The method takes into account the quality output of each STR, namely, perfect-work, acceptable-work, and defective-work as presented in Chapter 6. It is anticipated that the method provides Quality-Managers and Building-Inspectors with reliable information from which inspection efforts can be prioritized. In other words, greater effort may be expended to overcome causes, which have a high likelihood leading to the quality deviation for each STR and reduced attention of those with low likelihood.

The following chapter is an extension to the proposed classification in Chapter 6. In particular, the quality deviation for specific STR based on *the frequency of the expected output work*, namely, perfect, acceptable and defective work. The chapter discusses the development of a new model utilizing Bayesian Belief Network (BBN) to link the nature of task with the direct factors related to task's resources and surrounding conditions. The chapter presents a description of Bayes theorem and its applications providing a conceptual background on BBN on which the interpretation of the models has been. It also discusses the different metrics that were used in the development of the model, and examines the way BBN is used in the construction industry. The contribution of the chapter to knowledge is its discussion of the quality deviation and defects analysis using a suggested BBN model.

7.2 Background - Bayesian Belief Network (BBN)

The Bayesian framework (analysis) was developed with the aim of providing a practical illustration of knowledge for reasoning in uncertain situations. It was in 1921 that the representation was first presented by the researcher, Wright for examining crop failure (Wright, 1921). The framework was presented in various studies subsequently, using a variety of names (Hackerman & Wellman, 1995; Jensen, 1996; Majumdar, 2004; Marsh & Bearfield, 2007; Neapolitan, 2004; Neil, Fenton, & Tailor, 2005; Pearl, J., 2000; Spiegelhalter, Dawid, Lauritzen & Cowell, 1993; Winkler, 2003).

The Bayesian Belief Network (BBN) was originally formulated in the later part of 1970s in order to model the top-down (semantic) and bottom-up (perceptual) arrangement of evidence in reading (Conrady & Jouffe, 2011b). There was rapid development of Bayesian networks because of its capacity to make bi-directional inferences, along with an arduous probabilistic base. It soon took the place of preceding, ad hoc rule-based systems to become the key method for providing uncertain reasoning in Artificial Intelligence (AI) and expert systems (Conrady &

Jouffe, 2011b). Bayesian Belief Network (BBN) is also known as generative model, causal model and probabilistic cause-effect models.

The Bayes Theorem is used as the basis of all inferences carried out in BBN (Conrady, Jouffe & Elwert, 2014). Bayes Theorem entirely concentrates on how to review our beliefs keeping in view the latest evidence. Bayes Theorem can be demonstrated by first depicting two simple nodes as can be seen in Figure 7.1. These nodes signify the combined probability of the variables, evidence E and hypothesis H in a certain population. This case employs conditional probabilities of H, considering the values of its parent, evidence E.

Figure 7.1 A Bayes Theorem representing the statistical relationship between to two variables

When used in this form, Bayes Theorem mathematically illustrates how the conditional probability of event E, given H is linked to the converse conditional probability of H, given E. The Bayes Theorem is mathematically represented as follows:

$$P(H|E) = \frac{P\ (E\mid H)\ P\ (H)}{P\ (E)} \tag{7.1}$$

Where:

- P (H) denotes the prior probability of event H;
- P (E) denotes the prior probability of event E, and functions as a normalizing constant;
- P ($E|H$) refers to the conditional probability E, with given H. It is also known as likelihood.
- P ($H|E$) refers to the conditional probability of H, with E given. It is also known as the posterior probability since it is obtained from, or relies on the given value of E.

A Bayes theorem that has n nodes (i.e. events), in the order X_1 to X_n, is considered (see Figure 7.2). A certain value in the joint distribution is shown by $P(X_1 = x_1, X_2 = x_2, X_3 = x_3, \ldots, X_n = x_n)$, or in short, $P(x_1, x_2, x_3, \ldots x_n)$. Joint probabilities can be factorized using the chain rule of probability theory. Therefore,

$$P(x_1, x_2, x_3, \ldots, x_n) = P(x_1) \times P(x_2|x_1) \times P(x_3|x_1, x_2) \times \ldots \times P(x_n|x_1, x_2, \ldots, x_{n-1}) \quad (7.2)$$

$$P(x_1, x_2, x_3, \ldots, x_n) = \prod_i P(x_i|x_1, x_2, x_3, \ldots, x_{i-1}) \quad (7.3)$$

Figure 7.2 A Bayes Theorem representing the statistical relationship between to n nodes

When the structure of a Bayes theorem suggests that the value of a certain node is *only* dependent on the values of its parent nodes, then:

$$P(x_1, x_2, x_3, \ldots, x_n) = \prod_i P(x_i|Parents(X_i)) \quad (7.4)$$

For instance, the Bayes theorem for the conditional probability of x_3 given x_2 for n events $P(x_1, x_2, x_3, \ldots x_n)$, with $P(x_i) \neq 0$ for all i, and for $1 \leq i \leq n$, is illustrated as follows:

$$P(x_3|x_2) = \frac{P\ (x_2|x_3)P(x_3)}{P\ (x_2|x_1)P(x_1) + \ P\ (x_2|x_2)P(x_2) + \cdots + P\ (X|x_n)P(x_n)} \quad (7.5)$$

Bayesian analysis refers to the process of inductive reasoning. This kind of analysis allows for integrating the sample data as well as past information (expert judgement) to carry out inferences (Gelman et al., 2003). This can be accomplished by using Bayes' Theorem to develop posterior probability distributions for model parameters while carrying out the model learning process. Bayesian evaluation then involves a BBN (Winkler, 2003). BBN refers to graphical illustrations in which pairs of nodes are connected to each other through conditional probabilities. Analyses are carried out by BBN without requiring an entire set of values for all predictors. A BBN structure can be created from a dataset with help of a learning algorithm. The model structure can also be created by a domain professional who use a dataset to calibrate the unconditional and conditional probabilities. Ultimately, expert analysis is used to explain the model structure and the probability distributions (Gelman et al., 2003).

It needs to be mentioned that BBN does not involve any causal assumptions, the explanation is only statistical (informational) (Conrady & Jouffe, 2011b). The subsequent sections extensively elaborate on the BBN features and metrics.

7.3 BBN Model

The task of developing an illustration of a real world situation is called modeling (Millán et al., 2010). The formal nature of the Bayesian framework makes it possible to highlight the assumptions linking knowledge at various levels of abstraction (Gelman et al., 2003). The Bayesian inference over this model explains an ideal learner of abstract knowledge (Tenenbaum et al., 2006). Although actual learning is limited by resources, the workings of an ideal learner can reveal unexpected properties of the knowledge that can be acquired from the information available. In this section, the BBN features are recognized, including variables, structure, and inference with a few BBN metrics, after which the way BBN is used in construction projects is assessed. The research model is ultimately developed.

7.3.1 BBN variables

It is possible to disintegrate the variables into common states and values like nominal, binary, continuous and discrete on the basis of the nature of the phenomena being examined, or the properties of our measuring instrument (Conrady et al., 2014; Neapolitan, 2004).

- Binary (Boolean) – when there are just two states of the variable, it is known as binary (e.g. Yes & No or True & False);
- Nominal (labelled) – the states are written in the form of words, which cannot be converted into a numerical scale, (like short, tall, low, medium, high);

- Discrete – A finite set of values can be adopted by a discrete variable. The states include point real numbers, and each individual value of the variable is going to be classified as a state (such as 0, 1, 2, 3);
- Continuous – A continuous variable can adopt any value from the range provided. The states consist of intervals between real numbers, the values are believed to be numerical and are going to be discretized (such as -3~0, 0~0.5, 0.5~1, 1~5), etc. or point real numbers;

A Bayesian network in which both discrete and continuous variables are involved is known as a 'Hybrid Bayesian Network' (Russell & Norvig, 2003).

7.3.1.1 Conditional Probability Tables (CPT):

The preceding section explained the states (values) of the nodes involved in the Bayesian networks (BBN). The relationships between the linked nodes should then be quantified. This can be done by identifying a conditional probability distribution for each node (Neapolitan, 2004), which are explained as follows:

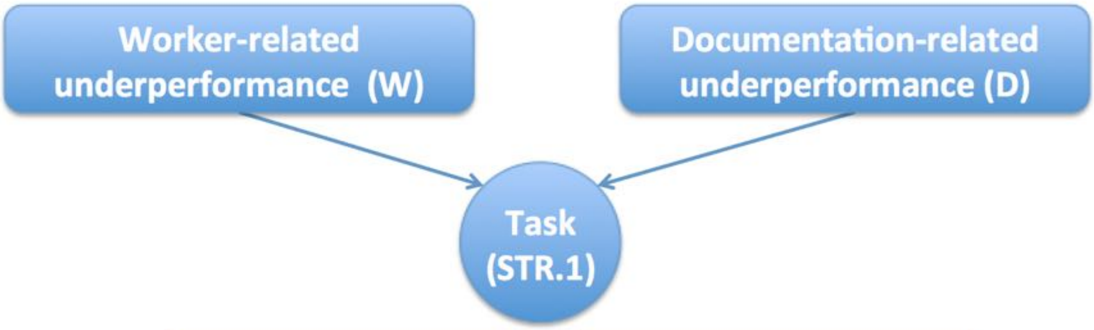
- Conditional Probability Tables (CPT) – for binary, nominal and discrete variables,
- Conditional Probability Distributions (CPD) – for continuous variables.

The Conditional Probability Tables (CPT) are used as expressions in this study with the goal of developing and constructing the research model on the basis of the nature of data set that comprises of binary and discrete variables (Neapolitan, 2004). Every node in a BBN should have a CPT linked to it. The likelihoods given by conditional probabilities are on the basis of past information, with all likely combinations of values of the parent nodes being given for each node. Each instantiation of parent values has a single row, which explains the likelihood that the child is going to adopt each of its values.

Figure 7.3 illustrates a simple example of the Conditional Probability Tables (CPT) of the states (values) of the variables (nodes) of the Bayesian networks (BBN). It is presumed for the sake of simplicity that there are just two states (occurred and not occurred) of the three nodes. The arc from 'worker-related underperformance' and ‘documentation-related underperformance’ to sub-task requirements ‘STR.1’ basically shows that the former has an effect on the latter. BBN is calculated by developing the Conditional Probability Tables (CPT) as shown in Figure 7.3.

Worker-related underperformance (W)	P(W)
Not Occurred	0.6
Occurred	0.4

Documentation-related underperformance (D)	P(D)
Not Occurred	0.2
Occurred	0.8



Task (STR.1)		P (STR.1 | W, D)	
(W)	(D)	Not Occurred	Occurred
Not Occurred	Not Occurred	0.8	0.2
Not Occurred	Occurred	0.9	0.1
Occurred	Not Occurred	0.6	0.4
Occurred	Occurred	0.3	0.7

Figure 7.3 Conditional Probability Tables (CPT) between the variables

Figure 7.3 shows that ‘worker-related underperformance’ and ‘documentation-related underperformance’ are direct cause variables which might lead to the quality deviations and defects to ‘STR.1’. In the example, the state of ‘worker-related underperformance’ node was observed to be ‘not occurred’ as a cause of problem was 0.6 and ‘occurred’ was 0.4 and the ‘‘documentation-related underperformance’ node was observed to be ‘not occurred’ was 0.2 and ‘occurred’ was 0.8. The meaning is that the probability of the ‘documentation-related underperformance’ node was observed to occurred was 0.8 double the probability of the ‘worker-related underperformance’ node, which equaled 0.4.

For the ‘STR.1’ state, the probability of the quality deviations and defects to occurr for ‘STR.1’ was 0.2 when the ‘documentation-related underperformance’ and ‘worker-related underperformance’ were observed to not occurred. In the second case, the probability of the ‘STR.1’ state was 0.1 where ‘documentation-related underperformance’ was observed to be not occurred and ‘worker-related underperformance’ was observed to be occurred. In the third case, the probability of the ‘STR.1’ state was 0.4 where the ‘documentation-related underperformance’ was observed to be occurred and ‘worker-related underperformance’ was observed to be not occurred. Finally, the probability of the ‘STR.1’ state is 0.7 where ‘documentation-related underperformance’ and ‘worker-related underperformance’ were observed to be occurred.

7.3.1.2 Target variables:

Target variables are used to create a model for objects of interest, especially those things for we require reasoning. They are also known as faults, particularly with respect to technical diagnosis (Millán et al., 2010). Normally those phenomena are modelled by target variables that are latent (cannot be observed), which implies that they cannot be directly measured.

7.3.1.3 Observations variables:

Observation variables, also known as evidence variables or tests, are used for modelling those phenomena that are observable, and normally give information related to target variables.

7.3.2 BBN structure

Once the variables have been defining, the structure of the model needs to be explained. For this purpose, variables (i.e. nodes) are connected through arcs (also known as links). Arcs are directed in Bayesian networks, and when an arc’s direction is altered, its meaning changes (Daly, Shen & Aitken, 2011). When a directed arc is used to link two nodes in a graph, one of the variables is called a parent (the antecedent), while the other is known as a child (the successor) (Figure 7.4). Normally when there is an arc moving from a variable X to a variable Y, it is shown that X is a direct cause of Y. When there is no arc between X and Y, it is suggested that X is not directly causing Y (and vice versa) (Daly, Shen & Aitken, 2011).

However, it is possible to connect variables using other variables, and in these cases, the central idea is that of conditional independence.

The diagnostic direction is frequently suggested (explicitly or implicitly) as an alternative method to the causal arc direction (Figure 4). Diagnostic direction shows the relationship between various pieces in a reasoner's knowledge (Millán et al., 2010). The observation variable is a parent of the target variable when this direction is being used. Therefore, it is assumed that the structure of the BN is explained with the help of a human expert (Neapolitan, 2004). Another alternative method that can be used is making inferences of the structure using a group of past cases.

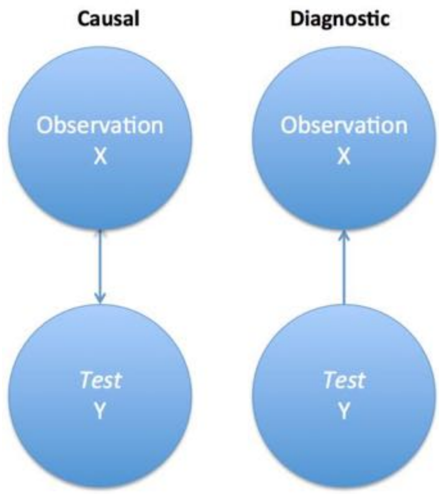


Figure 7.4 The two arc direction options

The possible arrangements of the three neighboring variables' independence relationships that exist in a BBN are shown in Figure 7.5. In the chain arrangement (also known as linear or serial), there is dependency between A and C when we are not aware of the state of B (Nadkarni & Shenoy, 2001; Neapolitan, 2004). After we find out the state of B, A and C become independent. The state of C is affected only by B's state, and no change in A is transferred to C (Millán et al., 2010). We can hence say that C is independent of A, when B is known.

The common cause arrangement (also known as diverging) shows dependency between B and C when the state of A is not known. Once we find out the state of A; B and C become independent (Nadkarni & Shenoy, 2001; Neapolitan, 2004). If we are not aware whether the common cause A is in effect or not, observing B modifies the likelihood of C and vice versa (Millán et al., 2010). Once A is observed, the effects are no longer dependent.

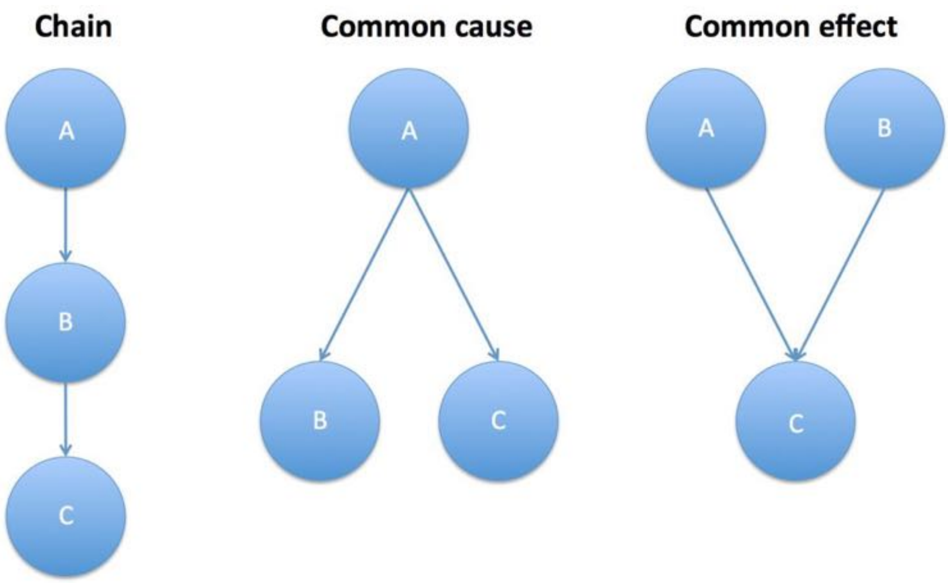


Figure 7.5 Possible configurations of three adjacent variables in a Bayesian network

The common effect arrangement (also known as converging) shows that A and B are independent when there is no observation with respect to the common effect C (Nadkarni & Shenoy, 2001; Neapolitan, 2004). Once the state of C becomes known, A and B become independent. When we know that the common effect is effective, observing one of the causes in effect is going to provide explanation for other causes (Millán et al., 2010).

7.3.3 BBN inference

BN can be used to explain the cases it is modelling once it has been created. The inference involved in the Bayesian model involves calculating the probability distribution over all variables, considering the evidence at hand (or a group of observations). This process is often called beliefs update. A posterior probability distribution is connected to each variable following beliefs update (Neapolitan, 2004). This distribution signifies the impact of evidence.

BNs inference makes it possible to have two types of reasoning: diagnostic and predictive inference (Millán et al., 2010). In diagnostic inference, the most probable causes are recognized from amongst a group of observations. In this context, observations are often called symptoms or faults. In contrast, predictive (or forecasting) inference tries to distinguish the most possible event occurrence from a set of observations. Diagnosis observes the past and the present to explain the present, whereas prediction looks at the past and present to explain the future (Neapolitan, 2004). Any variable in a BBN can either provide information (if its value is observed) or object of inference (considering the set of values adopted by other variables in the network) (Millán et al., 2010). Depending on the existing evidence, reasoning is going to be diagnostic or predictive in nature.

Different BBN metrics exist for the purpose of modelling, all of which essentially pertain to evaluating how network nodes are related and the comparative significance regarding the information gain transferred by the node to the knowledge of the target node (Millán et al., 2010; Neapolitan, 2004). These metrics are useful in comprehending and inferring the BBN framework as given below.

7.3.3.1 Statistical examination (Mean and independence Chi–square χ^2 test):

This shows the mean value of the nodes' observed variable. The following method is used to calculate each node's mean: when the values of nodes are linked to its state, the mean is obtained through them. However, if the node is continuous in nature, the mean is calculated from the intervals, whereas when the node is discrete with integer or real states, the mean is calculated using them.

Using the network over each variable and the target variable, the independence tests *Chi–square* χ^2 are carried out. The extent of freedom between each variable and the target variable in the network is denoted by the degree of freedom (*df*) (Pallant, 2010). In addition, the probability of independence between each variable and the target variable within the network is denoted by the p-value.

The mean values of the variables: 'worker-related underperformance' and 'documentation-related underperformance' for the observed variable: STR.1, for the example in figure 7.2, are 0.4000 and 0.8000 respectively (see Table 7.1). The independence tests *Chi–square* χ^2 indicates a significant association between 'worker-related underperformance' and the STR.1; χ^2 (1) = 15.1231, (p< 0.05), and an insignificant association between 'documentation-related underperformance' and the STR.1; χ^2 (1) = 0.1334, (p>> 0.05).

Table 7.1 Statistical analyses of the direct factors of STR.1

Node	Mean Value	*Chi–square* χ^2	*df*	p-value
Worker-related underperformance	0.4000	15.1231	1	0.0001
Documentation-related underperformance	0.8000	0.1334	1	0.7149

7.3.3.2 Prior probability value:

In this section, the findings of carrying out a simple example using the BayesiaLab 5.3 Software are presented so that the model suggested and the metrics used can be discussed. The histogram columns show the likelihood of obtaining all observed variables (i.e. 'worker-related underperformance', 'documentation-related underperformance' and 'STR.1') for the simple network in Figure 7.6.

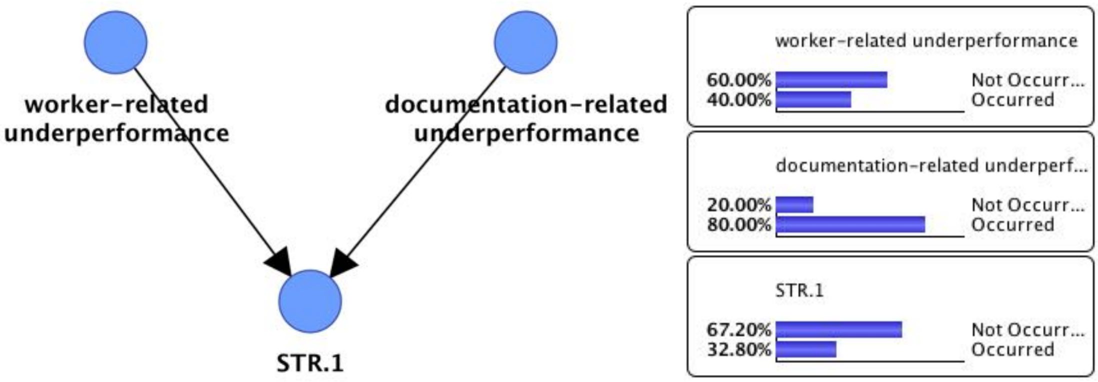


Figure 7.6 Prior probabilities value for the model

Without entering any observations, and uses just the past probabilities to forecast the likelihood that the quality deviation and defect taking place for STR.1 is equal to 32.80%. This is calculated with the help of equation 7.4 (each mix of 'worker-related underperformance' '*W*' and 'documentation-related underperformance' '*D*' are multiplied with the relevant conditional probability in STR.1) as shown below:

$P(STR.1|W,D)$

$$= P(W) \times P(D) \times P(STR.1|W,D) + P(W) \times P(\overline{D}) \times P(STR.1|W,\overline{D}) + P(\overline{W}) \times P(D) \times P(STR.1|\overline{W},D) + (\overline{W}) \times P(\overline{D}) \times P(STR.1|\overline{W},\overline{D})$$

$P(STR.1|W,D)$

$$= 0.40 \times 0.80 \times 0.70 + 0.40 \times \overline{0.20} \times 0.40 + \overline{0.60} \times 0.80 \times 0.10 + \overline{0.60} \times \overline{0.20} \times 0.20$$

$$P(STR.1|W,D) = 0.224 + 0.032 + 0.048 + 0.024 = 0.328 \approx 32.80\%$$

Where, $STR.1$: the quality deviation and defect is occurred; W: 'worker-related underperformance' to be direct cause is occurred; $\overline{W}$: 'worker-related underperformance' to be direct cause is not occurred; D: 'documentation-related underperformance' to be direct cause is occurred; $\overline{D}$: 'documentation-related underperformance' to be direct cause is not occurred. The model predicts that the probability that the quality deviation and defect is not occurred for STR.1 equals 67.20%. This is computed using the equation (7.4) as following:

$P(\overline{STR.1}|W,D)$

$$= P(W) \times P(D) \times P(\overline{STR.1}|W,D) + P(W) \times P(\overline{D}) \times P(\overline{STR.1}|W,\overline{D}) + P(\overline{W}) \times P(D) \times P(\overline{STR.1}|\overline{W},D) + (\overline{W}) \times P(\overline{D}) \times P(\overline{STR.1}|\overline{W},\overline{D})$$

$P(\overline{STR.1}|W,D)$

$$= 0.40 \times 0.80 \times 0.30 + 0.40 \times \overline{0.20} \times 0.60 + \overline{0.60} \times 0.80 \times 0.90 + \overline{0.60} \times \overline{0.20} \times 0.80$$

$$P(\overline{STR.1}|W,D) = 0.096 + 0.048 + 0.432 + 0.096 = 0.672 \approx 67.20\%$$

Where, $\overline{STR.1}$: the quality deviation and defect is not occurred.

7.3.3.3 Maximal positive/negative variation:

This measure (towards Maximal positive/negative variation) is used to suggest the variation between the priori model and the modal value when we are aware of the target variable value. In Information Theory, this measure denotes the number of 'bits' won which indicates the likelihood of X occurring once the target value is identified (BayesiaLab, 2010). The state that has the highest increase is represented by the *maximal positive variation* is, while the state with the highest decline is represented by the *maximal negative variation*. The following formula is used for *maximal variation*:

$$Maximal\,Variation = (\mathrm{P}(\mathrm{X} = \text{modal value} \mid \text{Target} = \text{observed value})) - (\mathrm{P}(\mathrm{X} = \text{modal value})) \tag{7.6}$$

When STR.1 has taken place (i.e. there has been quality deviation and defect in STR.1), and considering STR.1 to be the target node, there is variation in probability of the 'worker-related underperformance' to bring about an increase from 40% to 78.05%, while the 'documentation-related underperformance' showed an increase from 80% to 82.93% (see Figure 7.7).

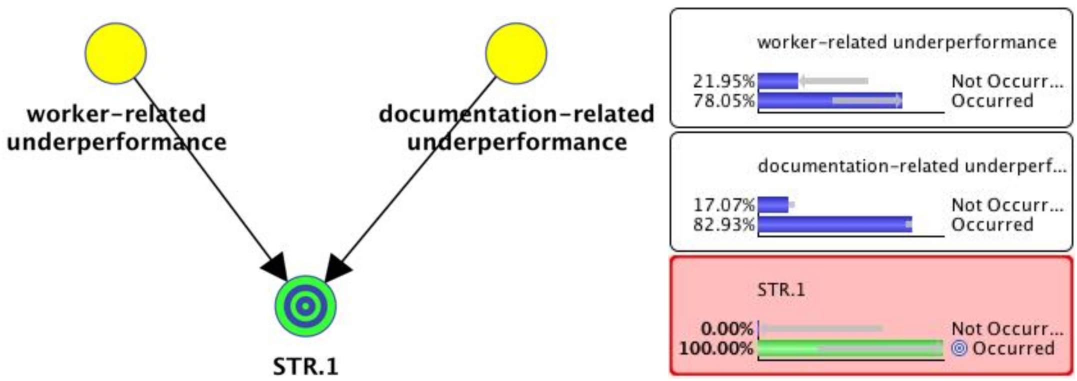


Figure 7.7 The observed that the STR.1 is occurred

This is computed using the equation (7.1 and 7.5) as following:

For the change of the probability of the 'worker-related underperformance'

$$P(STR.1|W) = P(D) \times P(STR.1|D,W) + P(\overline{D}) \times P(STR.1|\overline{D},W)$$

$$P(STR.1|W) = 0.80 \times 0.70 + 0.20 \times 0.40 = 0.56 + 0.08 = 0.64$$

$$P(W|STR.1) = \frac{P(STR.1|W) \times P(W)}{P(STR.1)} = \frac{0.64 \times 0.40}{0.328} = \frac{0.256}{0.328} = 0.7804$$

$$\approx 78.04\%$$

For the change of the probability of the 'documentation-related underperformance'

$$P(STR.1|D) = P(W) \times P(STR.1|W,D) + P(\overline{W}) \times P(STR.1|\overline{W},D)$$

$$P(STR.1|D) = 0.40 \times 0.70 + 0.60 \times 0.10 = 0.28 + 0.06 = 0.34$$

$$P(D|STR.1) = \frac{P(STR.1|D) \times P(D)}{P(STR.1)} = \frac{0.34 \times 0.80}{0.328} = \frac{0.272}{0.328} = 0.8292$$

$$\approx 82.92\%$$

Taking in account the STR.1 is the target node and its state is occurred, the *maximal positive variation* for 'worker-related underperformance' is computed using the equation (7.6) as following:

Maximal Variation = 78.04% - 40% = 38.04% ('worker-related underperformance' is occurred).

The *maximal positive variation* for 'documentation-related underperformance' is computed as following:

Maximal Variation = 82.92% - 80% = 2.92% ('documentation-related underperformance' is occurred).

Figure 7.8 shows that despite 'documentation-related underperformance' having a high probability of occurrence, however the *maximal variation* for 'worker-related underperformance' is greater, which indicates 'worker-related underperformance' is more likely to be the cause of quality deviation and defect for STR.1. Table 7.2 displays the *maximal positive/negative variation* for occurrence for STR.1.

Table 7.2 *Maximal positive/negative variation* for occurrence of STR.1

Node	*Priori Modal Value*		Modal Value		Maximal Variation	
	State	*%*	*State*	*%*	**Positive**	**Negative**
STR.1	**Scenario 1: Occurred**					
Worker-related underperformance	*Occurred*	*40.00%*	Occurred	78.04%	38.04%	38.04%
Documentation-related underperformance	*Occurred*	*80.00%*	Occurred	82.92%	2.92%	2.92%

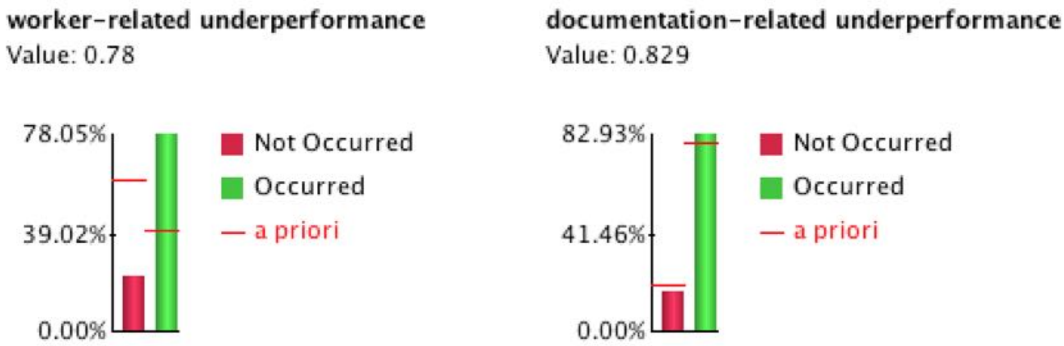


Figure 7.8 *Maximal variation* of the direct factors of STR.1 (Scenario 1: Occurred)

In contrast, Table 7.3 shows that taking in account the STR.1 is the target node and its state is not occurred, the *maximal positive variation* for 'worker-related underperformance' is computed using the equation (7.6) as following:

Maximal Variation = 18.45% ('worker-related underperformance' is not occurred).

The *maximal positive variation* for 'documentation-related underperformance' is computed as following:

Maximal Variation = 1.42% ('documentation-related underperformance' is not occurred).

Figure 7.9 shows that 'worker-related underperformance' having a high probability of non-occurrence, and the *maximal variation* for 'worker-related underperformance' is greater than 'documentation-related underperformance', which indicates 'worker-related underperformance' is more likely to non-occurrence of quality deviation and defect for STR.1. Table 7.3 displays the *maximal positive/negative variation* for non-occurrence for STR.1.

Table 7.3 *Maximal positive/negative variation* for non-occurrence of STR.1

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
STR.1	**Scenario 2: Not Occurred**					
Worker-related underperformance	*Not Occurred*	*60.00%*	Not Occurred	78.57%	18.54%	18.57%
Documentation-related underperformance	*Not Occurred*	*80.00%*	Not Occurred	78.57%	1.42%	1.42%

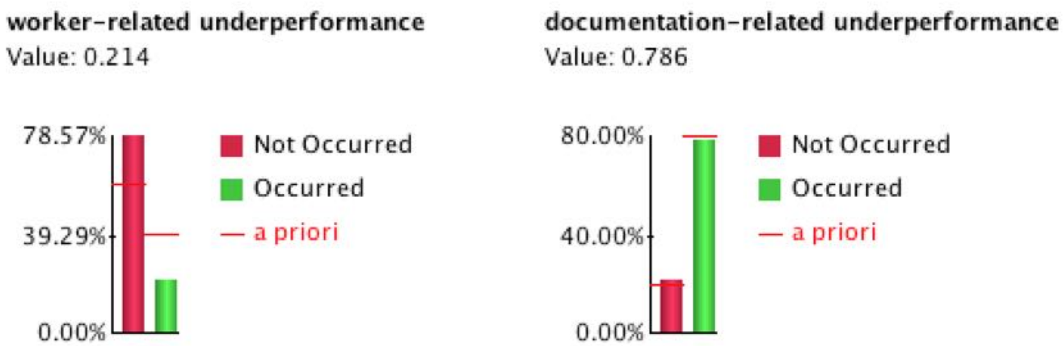


Figure 7.9 *Maximal variation* of the direct factors of STR.1 (Scenario 2: Not Occurred)

7.3.3.4 Direct Effect:

This enables calculating the direct impact De_x of definite variable X using the target node Y. The target variable Y is considered to be locally linear and the direct effect De_x is a calculation of the derivative of the target Y in terms of the variable X (Conrady & Jouffe, 2011a). The direct effect De_x denotes the effect of a slight variation of the "mean" of a variable X over the "mean" of the target Y, and refers to the ratio obtained. It can formally be explained as follows:

$$De_x = \frac{\delta_y}{\delta_x} \tag{7.7}$$

Where δ_x denotes the impact of a unit-change (i.e. mean) of variable X, while keeping all other variables constant ($\delta_x = X_1 - X_0$), and δ_y is the difference in the 'mean' of a target variable Y ($\delta_x = Y_1 - Y_0$) because of the variation in the change of variable X. For the example above, the change of the 'mean' of the 'worker-related underperformance' De_x is 0.52, where δ_y equals 0.12 at δ_x is 0 and δ_y equals 0.64 at δ_x is 100. On the other hand, the change of the 'mean' of the 'documentation-related underperformance' De_x is 0.06, where δ_y equals 0.28 at δ_x is 0 and δ_y equals 0.34 at δ_x is 100 (see Table 7.4).

Table 7.4 Direct Effects on Target STR.1

Node	δ_y at $\delta_x = 0$	δ_y at $\delta_x = 100$	Direct Effect De_y
Worker-related underperformance	0.12	0.64	0.5200
Documentation-related underperformance	0.28	0.34	0.0600

Figure 7.9 shows the direct effect De_x for 'worker-related underperformance' on the target node'STR.1' is higher than the direct effect for 'documentation-related underperformance'.

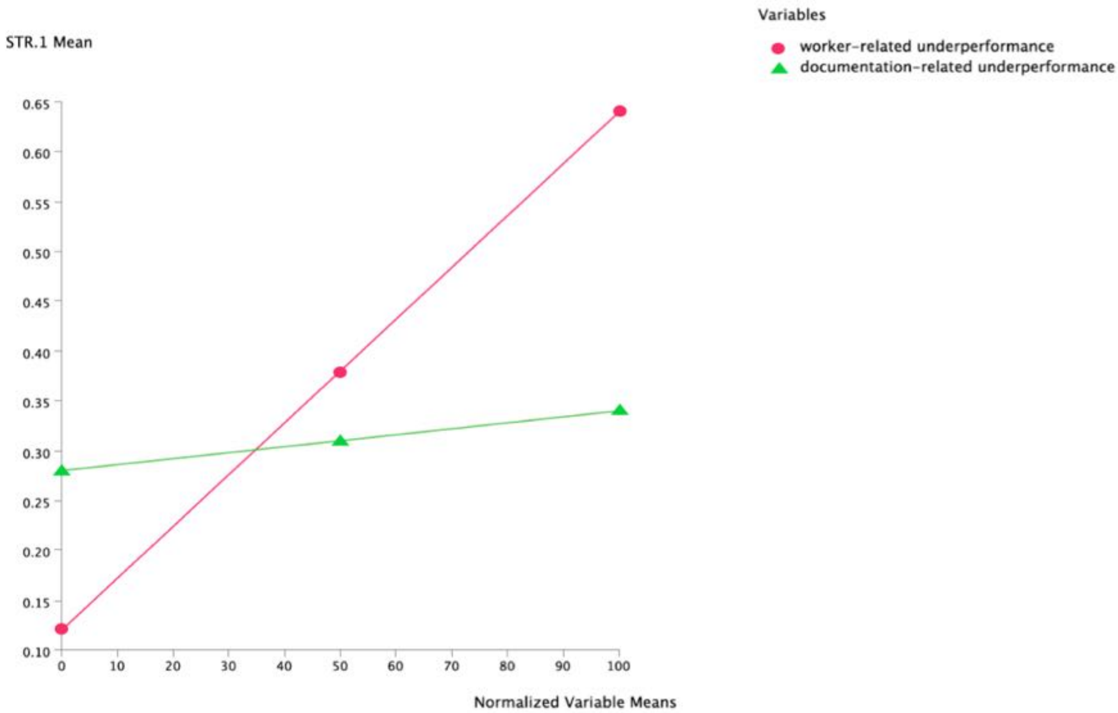


Figure 7.10 Direct effect for 'worker-related underperformance' and 'documentation-related underperformance' on the target node 'STR.1'

7.3.3.5 Mutual Information MI:

Mutual information MI provides information regarding the share of X and Y. It determines the extent to which the knowledge of one of the variables decreases uncertainty about the other variable (Jaladi & Devarapalli, 2012). MI also determines the extent of information provided by each variable to the target variable. For instance, when X and Y are independent, then being aware of X does not provide any information regarding Y and vice versa, hence their mutual information is nil. On the other hand, if X is a deterministic function of Y while Y is a deterministic function of X, then all of the information given by X is shared with Y: being aware of X gives the value of Y and vice versa (Kekolahti & Karikoski, 2013). In formal terms, the mutual relationship between the continuous random variables *X* and *Y* can be explained as follows:

$$I(X;Y) = \int_Y \int_X p(x,y) \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) dx\,dy \tag{7.8}$$

Where $p(x,y)$ refers to the joint probability *density* function of *X* and *Y*, $p(x)$ and $p(y)$ denote the marginal probability density functions of *X* and *Y* respectively (He, Guan & Qin, 2015; Zheng, 2010). With respect to the discrete random variables *X* and *Y,* a fixed summation substitutes for the double integral.

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) \tag{7.9}$$

Where $p(x, y)$ now refers to the joint probability distribution function of *X* and *Y,* and $p(x)$ and $p(y)$ denote the marginal probability distribution functions of *X* and *Y* respectively (Bonella, et al., 2009; Jaladi & Devarapalli, 2012).

Mutual information provides information regarding the intrinsic dependence shown in the joint distribution of *X* and *Y* compared to the joint distribution of X and Y that follow the assumption of independence (Church & Hanks, 1990; Jaladi & Devarapalli, 2012; Kekolahti & Karikoski, 2013). Mutual information hence measures dependence as follows: $I(X; Y) = 0$ if and only if *X* and *Y* are independent random variables. This can easily be observed in a single way: if *X* and *Y* are independent, then $p(x,y) = p(x)\,p(y)$, hence:

$$\log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) = \log 1 = 0 \tag{7.10}$$

In addition, there is non-negative $I(X;Y) \geq 0$ and symmetric $I(X;Y) = I(Y;X)$ mutual information (Bonella, et al., 2009; Church & Hanks, 1990).

Figure 7.10 provides the mutual information (MI) amount of information brought by 'worker-related underperformance' and 'documentation-related underperformance' to the target variable'STR.1'.

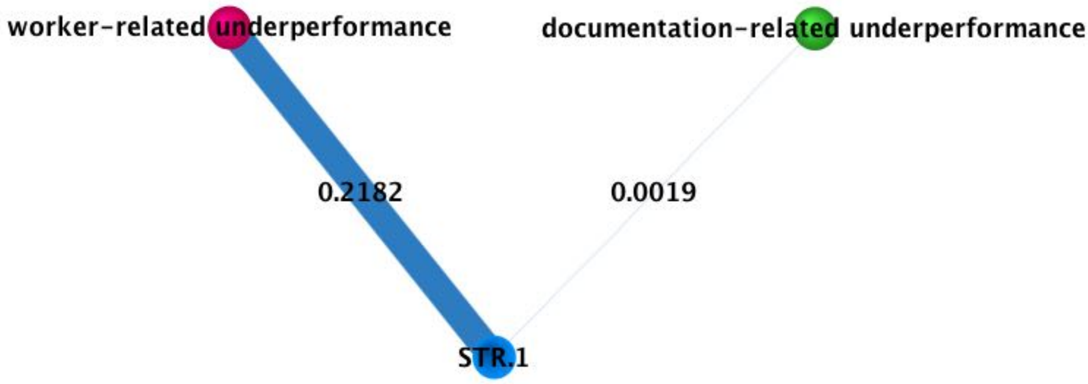


Figure 7.11 MI amount brought by 'worker-related underperformance' and 'documentation-related underperformance' to the 'STR.1'

The MI amount of information brought by 'worker-related underperformance' to the target variable'STR.1' is *I*('worker-related underperformance'; 'STR.1') = 0.2182, while, MI amount from 'documentation-related underperformance' to the target variable 'STR.1' is *I*('documentation-related underperformance'; 'STR.1') = 0.0019. This means that the relationship between 'worker-related underperformance' and 'STR.1' is dependent while between 'documentation-related underperformance' and 'STR.1' is independent.

7.4 Strengths and Limitations of Bayesian Belief Networks

The strengths of Bayesian belief networks BBN over alternative techniques (Fineman, 2010) are:

1. Explicit incorporation of uncertainty.
2. Forward and backward inference.
3. BNs are intuitive, conceptual and easily understandable. This helps at the development stage when the model is being discussed between the project manager and the various parties.
4. BNs can be used to perform sensitivity or "what-if" analyses to examine the sensitivity of predictions, or conclusions against initial assumptions.

5. BNs are capable of modelling highly complex systems. The areas of application mentioned earlier demonstrate this.
6. Ability to run with missing data.

These characteristics suggest that a BBN approach is more appropriate for causation analysis of quality deviation. Also, Bayesian belief networks BBN do have some limitations (Fineman, 2010):

1. Calculation time.
2. BN model is only as good as the modeller and experts who produced it, since it is a representation of the modeller and the experts' perceptions of reality. Therefore best fit is chosen given the modeller and experts.
3. Centres on the extent of the quality and reliability of the prior beliefs used in Bayesian inference processing.
4. Difficulty in empirically validating model estimates in models built only on expert knowledge.

7.5 Review BBN Models and Applications in Construction Projects

It is felt that discussion at this point of BBNs might be deemed relevant as a pre-cursor to this study’s findings (to somewhat supplement chapter 2). BBNs have become popular tools for supporting decision-making processes (Farmani et al., 2009; Panthi & Ahmed, 2015). They have been applied for the comparison of alternative management options, the analysis of adaptive management, resource management including resource quality management, and even in the diagnosis of disease (McKendrick et al., 2000). Other specific applications of BBNs include the prediction of student’s behavior who studies biology (McCann et al., 2006), and even the assessment of environmental and ecological risk (Marcot et al., 2006; Smith et al., 2007).

In construction industry, McCabe et al. (1998) developed a BN to improve modelling of construction performance. The BN was used to evaluate performance at each resource interaction/queuing location based on performance indices. Queue length index, queue wait time index, customer delay index, server utilisation index and server quantity index were the developed indices. Remedial action needs to be performed where values of any of the performance indices does not fall between the lower and upper bounds of the given indice. The cost and duration nodes were added to allow different approaches to be applied to performance diagnosis. Resource variables are those causal nodes that represent changes to the construction project that are within the control of the project manager. The causal variables in McCabe et al.'s model are the following Boolean nodes.

Fan and Yu (2004) incorporated BNs in a risk management decision support system. The pair based the incorporation on an assumption that if more resources were added to project activities the cost of these activities would increase while at the same time the risk would be lower. The BNs operate within a feedback loop that accommodates resources to control risks after data is observed and updated in the network.

Fineman (2010) consider quantification in a broader sense by measuring risk in the context of large projects. The authors provide(s) that conventionally risk is seen as an abstract concept, which is difficult to measure. Improved risk management offers the possibility to identify and control risks in such a way that the project is completed successfully despite risks. The team considered the time, cost and quality trade-offs that may be made in project risk management. The authors proposed the use of a causal risk framework based on BNs to mitigate classical modelling problems and enable better decision-making.

Lee et al. (2009) applied BNs to results of surveys conducted with 252 experts from 11 Korean shipbuilding companies for the purposes of better understanding large project risk management. The authors found that BN application helped to represent complex relationships and conditional probabilities of risk items, and for these reasons was a preferable risk management tool to influence diagrams and cross impact methods.

Nasir et al. (2003) applied BNs to the schedule of construction projects. Their model provides recommendations for upper and lower activity duration limits based on the characteristics of the project. Environment, geotechnical, labour, owner, design, area conditions, political, contractor, contractor non-labour resources and material were the ten categories for building construction schedules identified based on the literature and expert opinion. Nasir et al. identified detailed risk variables (n = 69 risks) within each category, and divided the risk variables into schedule risk variables and activity variables. The first type of variables were input nodes where the evidence may describe the project condition. The second type of variables were output nodes. Activity variables were divided into mobilization/demobilization, foundation/piling, labour intensive, equipment intensive, mechanical/electrical, roof/external, demolition and commissioning. Each group was modelled with two nodes where one node represented a pessimistic value and the other node represented an optimistic value.

Luu et al. (2007) later continued Nasir et al.'s work by applying BNs to the quantification of schedule risk in construction projects. They also modified McCabe et al.'s BN model where the sixteen most significant causes of schedule delay in construction projects in Vietnam were identified. Following this, the researchers established 18 cause and effect relationships based on expert opinion. The BN model developed was applied to two case studies, and performed well in predicting the probability of the construction schedule delay.

Khodakarami (2009) extended Nasir et al.'s work by presenting a general framework for the application of BNs to project scheduling using critical path method (CPM) calculations. The model provides a novel interpretation of activity criticality under uncertainty. Comparable to standard CPM, the criticality of an activity can be measured by its total float, that is, the difference between the Latest Finish and the Earliest Finish. Khodakarami proposed a BN model for the duration of a prototype activity to demonstrate how different types of uncertainty could be modelled, and concluded that activity duration depended directly on how much money is spent and/or what level of quality is achieved, and that trade-off exists between uncertainty associated with duration and uncertainty associated with cost.

Khalafallah et al. (2005) apply BNs to a system for estimating cost contingencies relevant to tender preparations. The team used the results of a survey of 22 factors believed to be associated with cost overruns in the residential construction sector to develop a risk-contingency model. The authors reported that the benefits of the model were that it avoided complexity such as high-level mathematical treatment and therefore was easier to apply than conventional approaches to estimating cost contingencies.

Hearty (2008) presented a risk analysis methodology integrating schedule and cost uncertainties through consideration of the effect of correlations. Conventionally, approaches dealing with correlation use a correlation matrix in input parameters. While conceptually correct, the number of correlation coefficients to be estimated grows combinatorially with the number of variables. Moreover, the analyst is forced to elicit values for the variances and the correlations from expert opinion where historical data are unavailable. Most experts are not trained in probability and have difficulty quantifying correlations. An alternative is the integration of BNs within an integrated cost-schedule Monte Carlo simulation (MCS) model. BN's can be used to implicitly generate dependency among risk factors and to examine non-additive impacts. The MCS is used to model independent events, which are propagated through BN's to assess dependent posterior probabilities of cost and time to completion. BN's can also include qualitative considerations and project characteristics when soft evidence is acquired. The approach builds on emerging methods of systems reliability.

Panthi and Ahmed (2015) applied BNs to analyzing construction accident reports for the purposes of preventing future accidents. The pair identified causal factors from a database of construction accidents and interactions amongst casual factors using data mining. The pair were able to quantify safety risk in a probabilistic form, and were further able to develop a predictive model from which preventive measures could be developed and applied proportionately.

There is lack of research applying BNs to quality deviation modelling in construction industry. A gap in the literature specifically appears to exist in relation to interaction between the requirements of construction tasks (the sub-task requirements) and the causes of quality deviation and defects. The next chapter discusses interaction between quality deviation and defects and the direct causes of such, and will introduce an approach to BN modelling.

7.6 BBN Specific Research Model Structure

The aim of the research is to apply a BBN approach to the assessment of the relationship between STRs and quality deviation. As mentioned in Chapter 3, seventeen STRs forming a column member were used as cases to analyze each STR's respective sensitivity towards the quality deviation. Each STR is understood in terms of its description in relevant building codes and the most minute level of specification from such building codes is applied (see Figure 7.12, repeating its earlier introduction in Fig 1.1). Figure 7.12 also presents the division of project phases into a number of STRs through the use of WBS and hierarchy technique. The analysis is narrowed from super-structure phase, to building element (column), to project task (rebar), and then to sub-task 1 (tie fabrication), and then to the specific sub-task requirement (tie width/depth, bend, hooks). As mentioned, the results of quality output, namely, perfect, acceptable or defective-work for each STR were provided in Chapter 6 (described in Figure 7.12 directly below, which re-contextualises the previously presented Figure 1.1).

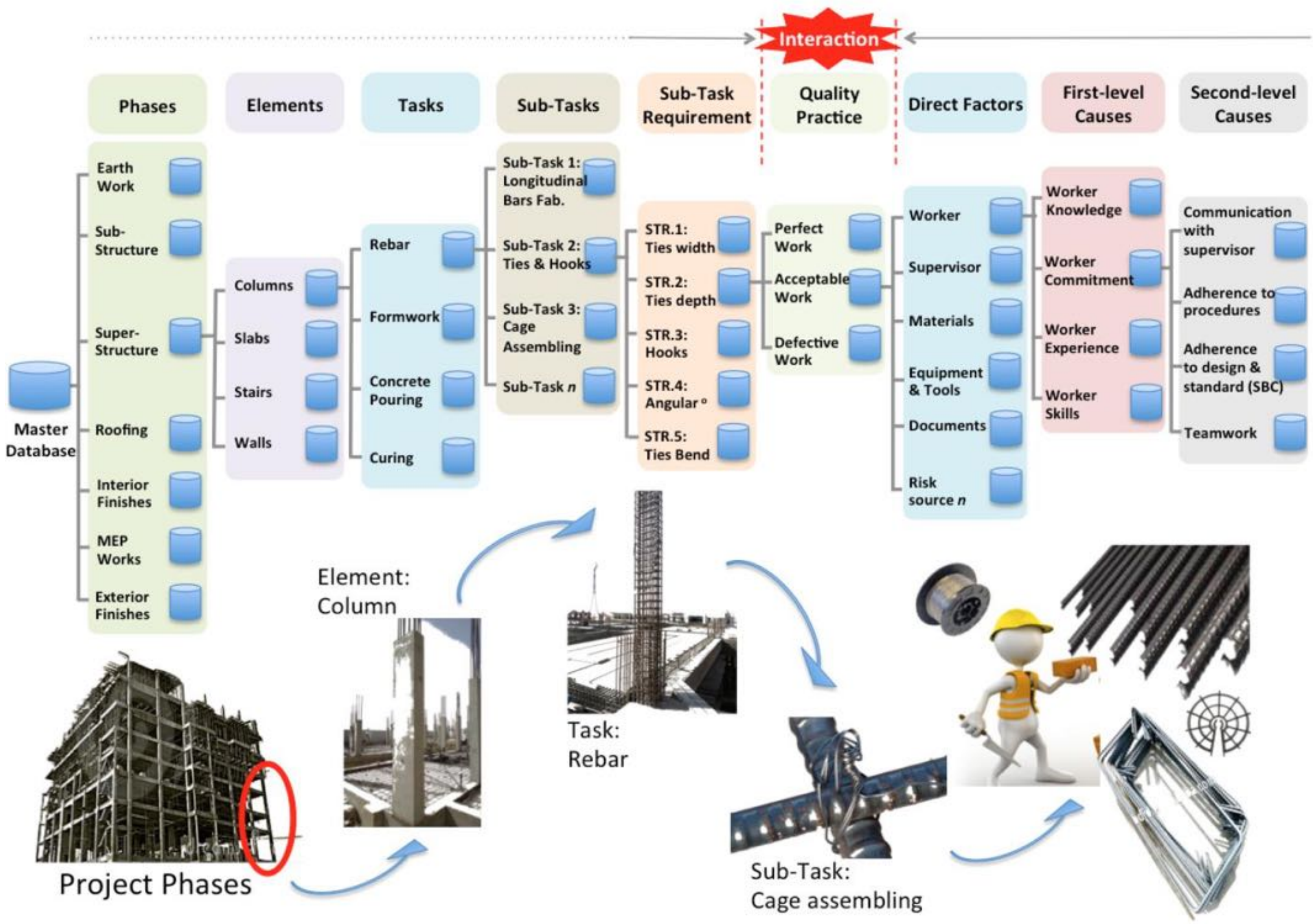


Figure 7.12 Project dividing into small events and their quality output and causes

The structure proposed in this research for categorizing the causes of the quality deviation is based on classification systems from previous studies. As mentioned in Chapter 2, Brunsson (1985, cited in Josephson & Hammarlund, 1999) proposed a series of construction defect events model, which the author argued that the phenomenon of defects could be best understood as a series of events. Fayek et al. (2004) applied a cause and effect method, namely, fish-bone classification diagram, to analyze quality deviation in construction projects (Construction Owners Association of Alberta [COAA], 2002; Love, 2002). The method is based on mapping first-level, second-level, and third-level causes and aims to present complex relationships in an effective manner. The principles of the general approach were adopted for the present study (see Figure 7.13).

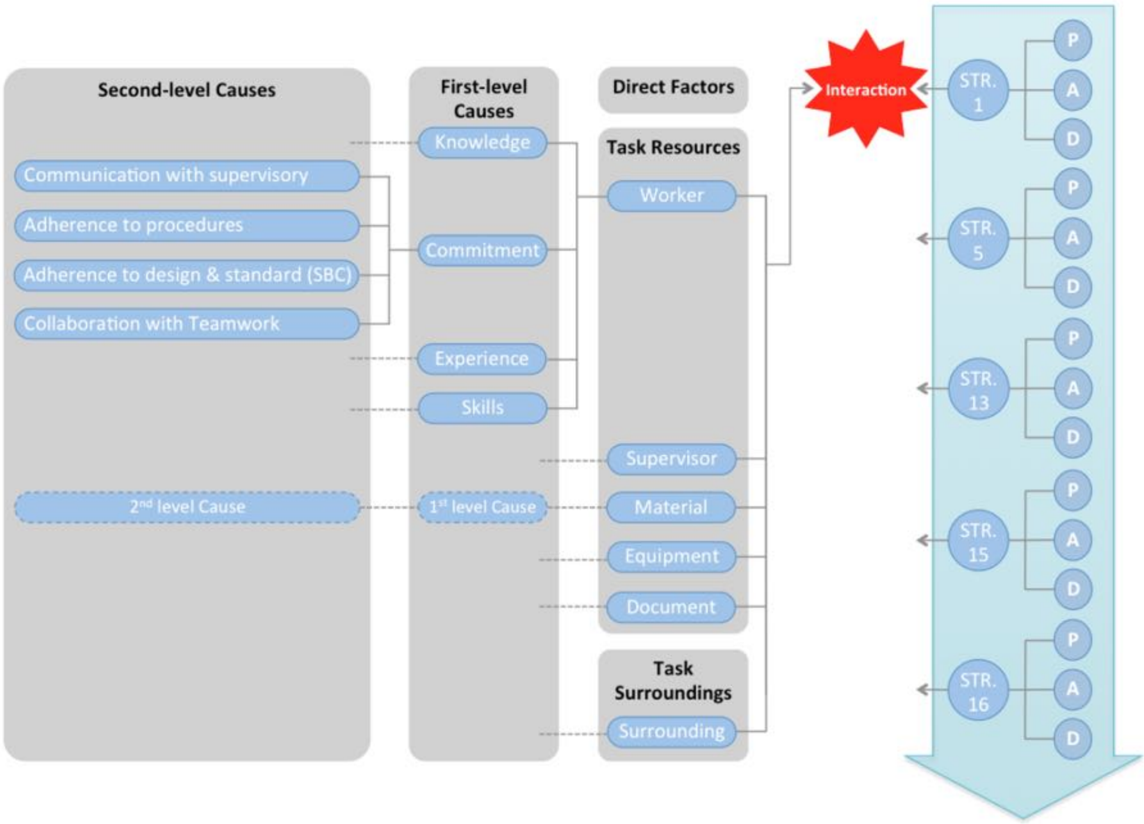


Figure 7.13 The structure proposed

In this research, factors considered in direct contact with STR were categorized into 'Task Resources', which included worker, supervisor, materials, equipment and documents; and 'Task Surrounding Conditions' as shown in Figure 7.13. Together such factors were referred to as 'Direct Factors'. Such factors were considered to directly interact with each STR with the output based on the interaction leading to varying degrees of quality practice, as classified as perfect, acceptable or defective-work. Following 'Direct Factors' are 'First-level Causes' and 'Second-level Causes'. The following diagram (Figure 7.13) shows that STR.1 has a number of Direct Factors (such as worker), First-level Causes (such as worker commitment) and the determinants of such causes referred to as 'Second-level Causes' (such as 'Adherence to procedures'). In Chapters Five and Six, 17 STRs were described in terms of their sensitivity towards deviation. Due to the complexity of each network and practical constraints, 5 out of the 17 STRs were investigated in terms of their application to the model proposed in this chapter. STR.1, STR.5, STR.13, STR.15, and STR.16 are shown in Figure 7.13. It was considered that five would be a sufficient numbers of cases in light of previous studies (Yin, 2009).

The quality practices (i.e., perfect-work, acceptable-work or defective-work) for each STR was analyzed in terms of its direct factors, first-level and second-level causes. Figure 7.14 following shows the state of the quality output of STR.1 is 'defective-work' and the likely direct factors to be occurred based on their frequency are 'worker' or 'material'. For the first-level causes, there was a high probability that 'commitment' would affect worker performance. 'Commitment with design dimensions' was found to be the most relevant second-level cause occurring and affecting worker 'commitment'. The research framework/model is further explained in Chapter 8.

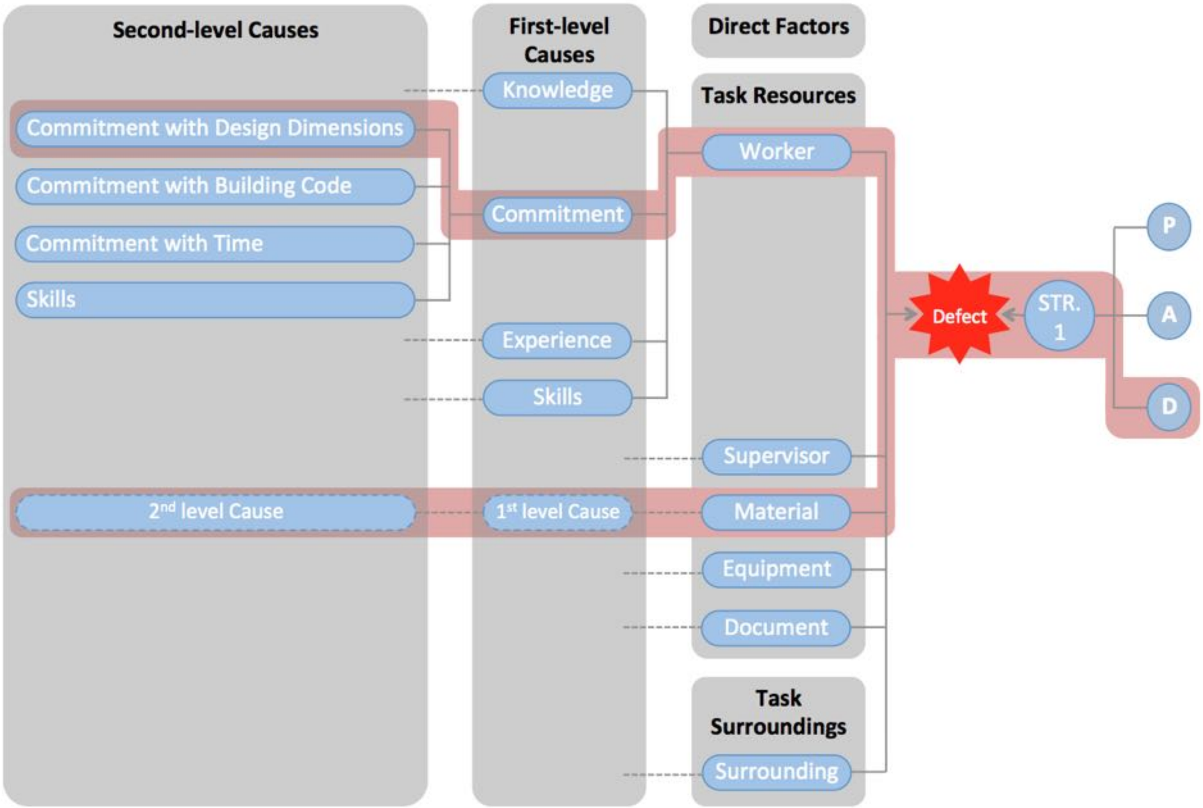


Figure 7.14 The state of the quality output of STR.1 is ‘defective-work’

7.7 Registering the Causes for Quality Deviation

As BayesiaLab 5.3 was used for the analysis, the registration procedure of the data on the model was as follows. First, probability distributions of the second-level causes were registered as single variables based on their frequency occurrence from the data collected through structured interviews with workers/supervisors, direct observations of performance, reviews of related project documentation (i.e., drawings and specifications) and measuring/observing the surroundings conditions. Table 7.5 shows that the probability distribution of the second-level cause ‘Design dimensions required’ for the ‘knowledge’ of the worker (i.e., the first-level causes) is 40% (2 of 5) for state of ‘occurred’ and 60% (3 of 5) for state of ‘not occurred’.

Secondly, probability distributions for first-level causes were registered based on the combination of the frequency occurrence of the second-level causes. If one or both of the second-level causes (e.g., ‘Design dimensions required’ and ‘Tolerance required’) was observed as ‘occurred’, the state of the first-level causes ‘knowledge’ was registered as ‘occurred’ (see Table 7.5). In contrast, the state of the first-level causes ‘knowledge’ was registered as ‘not occurred’ only if both of the second-level causes observed as ‘not occurred’ (see Table 7.5). The probability distribution of the first-level cause ‘knowledge’ is 80% for state of ‘occurred’ and 20% for state of ‘not occurred’.

Table 7.5 The probability distribution for first-level causes

	Second-level cause for ‘knowledge’		**First-level cause for ‘worker’**	**Second-level cause for ‘commitment’**		**First-level cause for ‘worker’**
	Design dimensions required	**Tolerance required**	**Knowledge**	**Adherence to procedures**	**Adherence to design & standard SBC**	**Commitment**
1	Occurred	Not Occurred	Occurred	Occurred	Not Occurred	Occurred
2	Not Occurred	Occurred	Occurred	Not Occurred	Occurred	Occurred
3	Not Occurred	Occurred	Occurred	Not Occurred	Not Occurred	Not Occurred
4	Not Occurred	Not Occurred	Not Occurred	Not Occurred	Not Occurred	Not Occurred
5	Occurred	Occurred	Occurred	Occurred	Occurred	Occurred

The probability distributions of direct factors were registered based on the combination of the frequency occurrence of the first-level causes. So, the probability distribution of the direct factors ‘worker’ for STR is 80% for state of ‘occurred’ and 20% for state of ‘not occurred’ as shown in Table 7.6.

Finally, the probability distribution of each STR was registered based on the interaction of the frequency occurrence of direct factors and quality practices (i.e., perfect-work, acceptable-work or defective-work) as described in the previous chapter. If 'perfect-work' occurred two times and the state of the direct factor ‘worker’ was ‘not occurred’ initially and was ‘occurred’ the second time, the frequency occurrence of the direct factor ‘worker’ was observed 50% to be direct factor and 50% to be not direct factor for the pattern of 'perfect-work' for the STR (as shown in Table 7.6). However, the frequency occurrence of the direct factor ‘worker’ for both 'acceptable-work' and 'defective-work' only observed to be ‘occurred’ 100%. This means the direct factor ‘worker’ is highly sensitive and often leading to quality deviations and defects. This procedure will be used for the registration of the data on the research model as described next chapter.

Table 7.6 The probability distribution of each STR

	First-level cause for 'worker'	First-level cause for 'worker'	Direct factor for STR	STR
	Knowledge	**Commitment**	**Worker**	
1	Occurred	Occurred	Occurred	Acceptable work
2	Occurred	Occurred	Occurred	Defective work
3	Occurred	Not Occurred	Occurred	Acceptable work
4	Not Occurred	Not Occurred	Not Occurred	Perfect work
5	Occurred	Occurred	Occurred	Perfect work

The majority of factors were differentiated on their state, namely, 'occurred' or 'not occurred.' Examples include 'adherence to procedures', and 'adherence to design & standard SBC'. However, other factors such as experience of workers were divided into 'high', 'medium', and 'low.' Wind speed (seconds per metre) was calculated with an instrument and data was divided into 'W<3' (three seconds per metre) 'W3-7' and 'W>7'. The results of these procedures are provided in the following chapter.

7.8 Chapter Summary

In this chapter we have reviewed Bayes Theorem and how it is used when building BBN. This chapter has provided an introduction to BBN and the different types of BBN structure in order to enable further contextualisation and background understanding for the model development to come. Also, some statistical metrics have been discussed related to the research model, alongside review of the advantages and the disadvantages of BBN; the structure proposed that would be used in this research has been explained. The registration procedure of the data set on the model, based on the Software program BayesiaLab 5.3, has been discussed. In the next chapter, discussion shall describe application of the BBN models, which address the quality deviation from standard norms, and defects analysis, as well as BBN models' validity.

CHAPTER 8: Analysis of Quality Deviations and Defects Using a Bayesian Belief Network BBN Technique

8.1 Introduction

Overcoming the quality deviation and defects for construction projects, in particular for the sub-task requirements, depends on identifying and classifying the most significant causes that previously experienced high variation of the quality practice, especially those who leads serious problems. This leads to understand their patterns and limit the likelihood of their occurrence through controlling the most sensitive causes via proactive actions in order to improve the system processes. On the basis of this principle, Chapter 5 examined 17 STRs using statistical process control analysis to identify the most sensitive STR towards the quality deviation and defects issues. As a complementary work, Chapter 6 introduced a new classification system able to apply on all STRs to determined which quality practices outputs (i.e., perfect-work, acceptable-work or defective-work) that has highest frequency across all STRs.

This chapter is an extension for previous work on chapters 5 and 6. The BBN approach was utilized to quantify the most significant causes through observing and predicting of the interaction between the deviation level in terms of the quality practices for each STR and which kind of causes that related to this deviation. Based on the statistical examinations and metrics include the significant association between variables, direct affect and mutual information be side the of the maximal variation values, the significant causes for five different STRs will be identified using data set includes 135 cases for each STR from 27 construction projects. Such deep patterns insights, which inherent of each STR, are expected to detect implicit prevention and proactive strategies that help to control the quality deviation and defects through prioritize for the most significant causes for each STR in order to improve overall quality and inspection system.

8.2 The Bayesian Belief Network BBN Model

Based on the presented structure of the STR in Chapter 7 (Figure 7.12 – 7.13) and its direct factors, first-level and second-level causes, the research model has been built as shown in figure 8.1. This structure has been applied for five STRs (STR.1, STR.5, STR.13, STR.15 and STR.16), as mention in chapter 7. The data used as input for BayesiaLab 5.3 based on the frequency occurrence of the variables form the data collected through the structured interview with the worker/supervisor, direct observation on their acts, review the related project documentation (i.e., drawings and specifications) and measuring/observing the surroundings conditions.

At the beginning, the interaction between the nature of each STR in terms of the quality variation (i.e., perfect, acceptable or defective work) and the direct factors is reviewed: the task resources and the task surroundings will be analyzed to identify which direct factors are more sensitive for the quality variation. For example, Figure 8.1 shows the interaction between STR and all direct factors 'worker', 'supervisor', 'materials', 'equipment and tools', 'documentation' and 'surroundings condition'. At this stage, the most significant factors will be determined. Next, the first-level causes will focus only on those factors that have high sensitive with the quality variation for STR. Finally the second-level causes will focus only on those first-level causes that have high sensitive with the determined direct factors. Model validity will be conducted end of this chapter. Recommendations for the quality practices will be discuss based on the results generated from this analysis.

Figure 8.1 STR model using BBN

8.3 Result Analysis

8.3.1 STR.1

8.3.1.1 Direct Factors with STR.1

8.3.1.1.1 Statistical examination for direct factors with STR.1

Table 8.1 provides prior probability values, before entering observations, and mean values of direct factors (e.g., ‘worker-related underperformance’, ‘supervisor-related underperformance’, ‘materials-related problems’, ‘documentation-related underperformance’ and ‘inappropriate surroundings conditions’) based on their own states for the observed target node STR.1.

The independence tests *Chi–square* χ^2 show a significant association between ‘documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ with the STR.1; χ^2 (2) = 10.508, (p< 0.05); χ^2 (2) = 5.7593, (p< 0.05) and; χ^2 (2) = 4.4551, (p< 0.05) respectively (as shown in Table

8.1). The *Chi–square* χ^2 test results for the remaining direct factors, namely, 'worker-related underperformance' and 'inappropriate surroundings conditions' failed to show a significant association ($p >> 0.05$).

The results support that only 'documentation-related underperformance', 'supervisor-related underperformance' and 'materials-related problems' are significantly associated with STR.1 performance.

8.3.1.1.2 Direct Effect

The direct effect, *De,* of direct factors on the target node STR.1 are listed in Table 8.1. 'Documentation-related underperformance', 'supervisor-related underperformance' and 'materials-related problems' were found have highest direct effect on the target node STR.1, at 0.2276, 0.4827 and 0.4002 respectively. Figure 8.2 shows the direct effect *De* of all direct factors on the target node'STR.1'. It also shows that 'documentation-related underperformance', 'supervisor-related underperformance' and 'materials-related problems' are higher than the other direct factors.

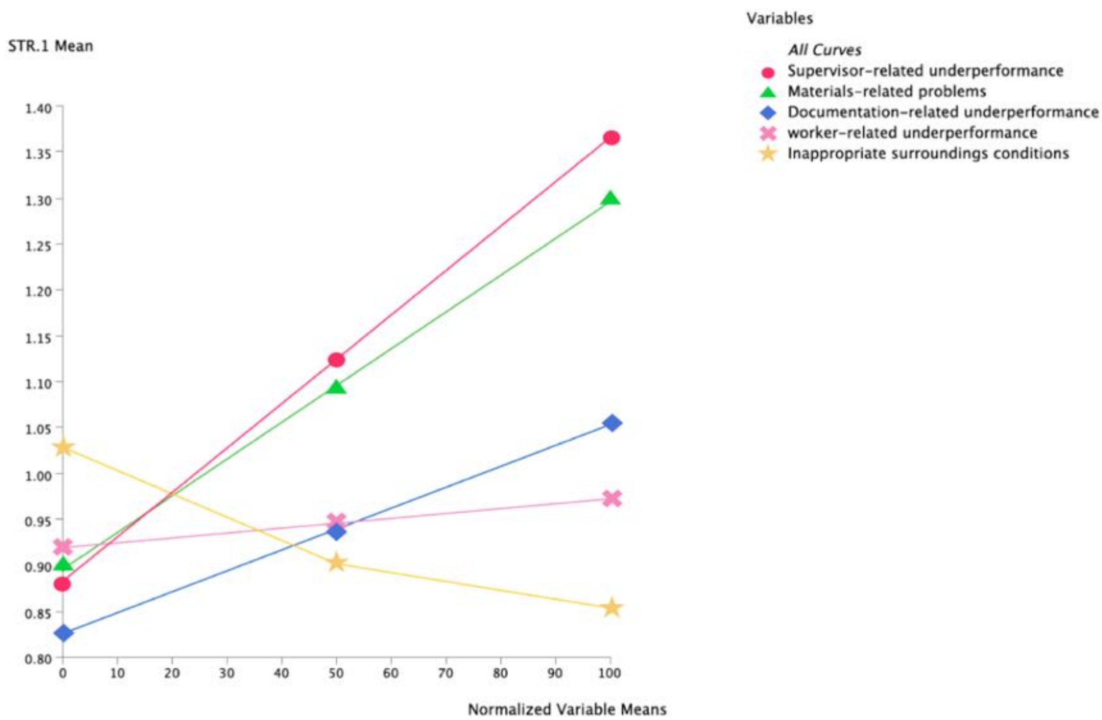


Figure 8.2 Direct effects of the potential causes of STR.1

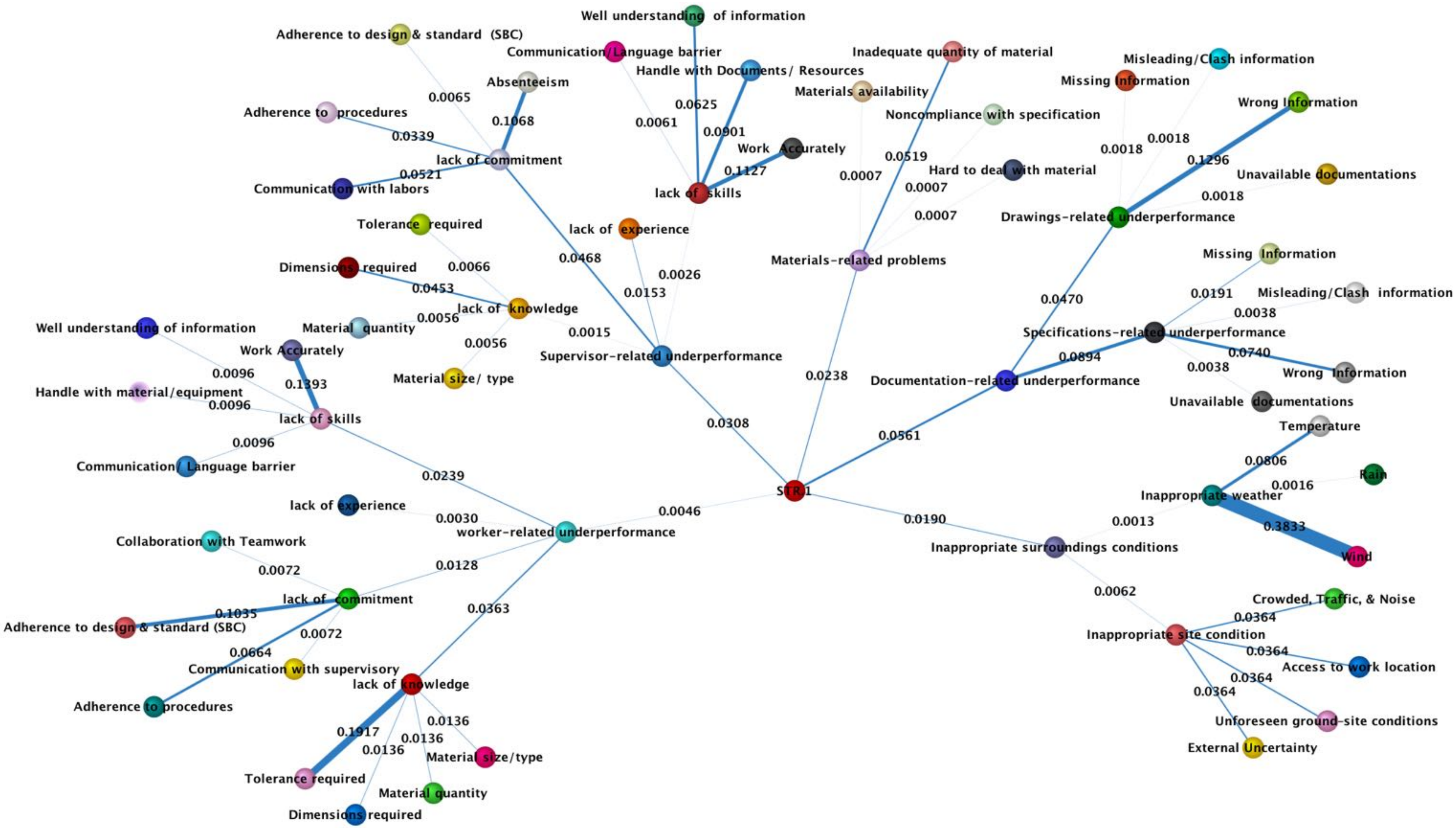


Figure 8.3 MI of STR.1 network

Table 8.1 Statistical analyses of the significant direct factors of the STR.1

Node	Priori Modal State & Value			Mean	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred		*Occurred*	μ					
Documentation-related underperformance	55.39%		44.61%	0.4461	10.508	2	0.0052	0.2276	0.0561
Supervisor-related underperformance	90.83%		9.17%	0.0917	5.7593	2	0.0562	0.4827	0.0308
Materials-related problems	92.16%		7.84%	0.0784	4.4551	2	0.0107	0.4002	0.0238
Worker-related underperformance	84.87%		15.13%	0.1513	0.8517	2	0.6532	0.0532	0.0046
	Low	**Medium**	**High**						
Inappropriate surroundings conditions	32.72%	34.14%	33.14%	1.0042	3.5507	4	0.4702	-0.0873	0.0190

8.3.1.1.3 Mutual Information MI

Measurements of MI between each direct factor and target variable STR.1 are presented in Table 8.1. MI amount of information brought by the direct factors to the target variable 'STR.1' was *I*('documentation-related underperformance'; 'STR.1') = 0.0561, *I*('supervisor-related underperformance'; 'STR.1') = 0.0308, *I*('materials-related problems'; 'STR.1') = 0.0238, *I*('inappropriate surroundings conditions'; 'STR.1') = 0.0190, and *I*('worker-related underperformance'; 'STR.1') = 0.0046.

'Documentation-related underperformance', 'supervisor-related underperformance' and 'materials-related problems' have the highest MI with STR.1 indicating a more dependent relationship between these direct factors and the target variable. The MI of the other direct factors was small, which can be interpreted nearly as independent relationship. Figure 8.3 shows the MI amount of the 'STR.1'network.

8.3.1.1.4 Maximal positive/negative variation

The maximal variation of the significant direct factors, namely, 'documentation-related underperformance', 'supervisor-related underperformance' and 'materials-related problems', as shown in the previous tests: the *Chi–square* χ^2 test, direct effect and the mutual information MI was calculated. However, all direct factors were presented in Appendix B. Taking in account the node STR.1 as the target variable, the change of the probability of each direct factor is presented in Table 8.2 and is displayed in histogram columns in Figure 8.4 (a, b & c).

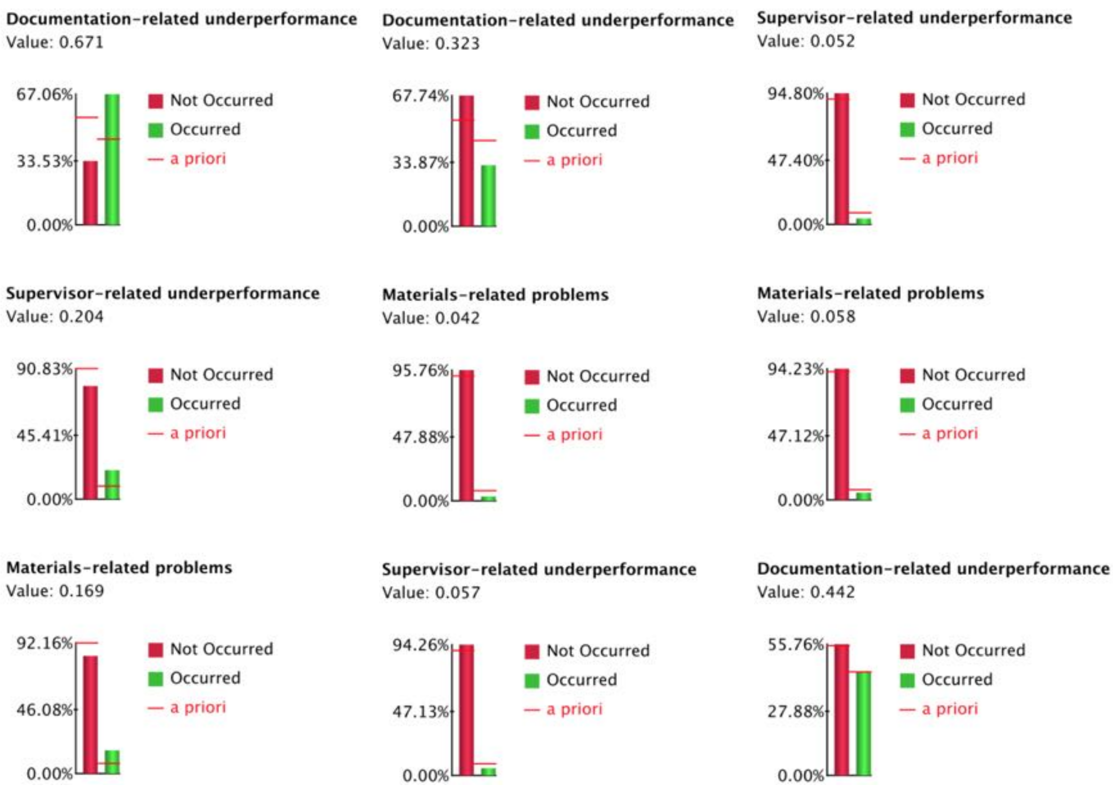
Table 8.2 Maximal variations of the significant direct factors of STR.1

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
STR.1	**Scenario 1: Defective work**					
Documentation-related underperformance	*Not occurred*	*44.61%*	*Occurred*	67.06%	22.44%	22.44%
Supervisor-related underperformance	*Not occurred*	*9.17%*	*Occurred*	20.43%	11.25%	11.25%
Materials-related problems	*Not occurred*	*7.84%*	*Occurred*	16.94%	9.098%	9.098%
STR.1	**Scenario 2: Acceptable work**					
Documentation-related underperformance	*Not occurred*	*55.39%*	*Not occurred*	67.73%	12.34%	12.34%
Supervisor-related underperformance	*Not occurred*	*90.82%*	*Not occurred*	94.25%	3.430%	3.430%
Materials-related problems	*Not occurred*	*92.15%*	*Not occurred*	95.75%	3.599%	3.599%
STR.1	**Scenario 3: Perfect work**					
Documentation-related underperformance	*Not occurred*	*55.39%*	*Not occurred*	55.76%	0.371%	0.371%
Supervisor-related underperformance	*Not occurred*	*90.82%*	*Not occurred*	94.79%	3.969%	3.969%
Materials-related problems	*Not occurred*	*92.15%*	*Not occurred*	94.23%	2.075%	2.075%

Performance of STR.1 could be ‘perfect-work’, ‘acceptable-work’ or ‘defective-work’. When ‘defective-work’ was observed (i.e., the state of the quality output for executing STR.1 is defective-work), the model predicted that the probability of ‘documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ occurrence increased. The maximal variation was 22.44%, 11.25% and 9.098% respectively (positive variation) (as shown in Table 8.2 and Figure 8.4 (a)). ‘Documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ are direct factors most prone to cause ‘defective-work’ in relation to STR.1.

When ‘acceptable-work’ was observed (i.e., the state of the quality output for executing STR.1 is acceptable-work), the model predicted that the probability of ‘documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ occurrence decreased. The maximal variation was 12.34%, 3.430% and 3.599% (negative variation) respectively (as shown in Table 8.2 and Figure 8.4 (b)). ‘Documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ are direct factors less prone to cause ‘acceptable-work’.

Similarly, when ‘perfect-work’ was observed (i.e., the state of the quality output for executing STR.1 is perfect-work), the model predicted that the probability of ‘documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ occurrence decreased. The maximal variation was 0.371%, 3.969% and 2.075% (negative variation) respectively (as shown in Table 8.2and Figure 8.4 (c)). ‘Documentation-related underperformance’, ‘supervisor-related underperformance’ and ‘materials-related problems’ are direct factors less prone to cause ‘perfect-work’.



(a) Defective work (b) Acceptable work (c) Perfect work

Figure 8.4 *Maximal variation* of the direct factors of STR.1

8.3.1.2 First-level Causes of the Direct Factors 'Materials-related Problems'

8.3.1.2.1 Statistical examination of the first-level

Table 8.3 provides prior probability values, before entering observations, and mean values of the first-level causes (i.e., 'materials availability', 'inadequate quantity of material', 'noncompliance with specification' and 'hard to deal with material') based on their own states of the observed direct factor 'materials-related problems'. The independence tests *Chi–square* χ^2 shows a significant association between first-level cause 'inadequate quantity of material' and direct factor 'materials-related problems'; χ^2 (1) = 9.7186, (p<< 0.05) (as shown in Table 8.3).

The independence tests *Chi–square* χ^2 for the remaining first-level causes failed to show a significant association with direct factor 'materials-related problems' (p>> 0.05). 'Inadequate quantity of material' is significantly associated with 'materials-related problems'.

Table 8.3 Statistical analyses of the significant causes of materials-related problems

Node	*Priori Modal Value*		Mean μ	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*						
Inadequate quantity of material	82.00%	18.00%	0.1800	9.7186	1	0.0018	0.2072	0.0519
Noncompliance with specification	99.26%	0.74%	0.0074	0.1333	1	0.7150	-0.0724	0.0007
Materials availability	99.26%	0.74%	0.0074	0.1333	1	0.7150	-0.0724	0.0007
Hard to deal with material	99.26%	0.74%	0.0074	0.1333	1	0.7150	-0.0724	0.0007

8.3.1.2.2 Direct Effect

The direct effect *De* of the first-level causes on direct factor 'materials-related problems' is listed in Table 8.3. 'Inadequate quantity of material' was found have highest direct effect, 0.2072. Figure 8.5 provides the direct effect *De* of the first-level causes and it clearly shows 'inadequate quantity of material' as higher than the other causes.

8.3.1.2.3 Mutual Information MI

Measurements of MI amount brought by first-level causes to the direct factor 'materials-related problems' are listed in Table 8.3 and displayed in Figure 8.3. MI amount of the 'inadequate quantity of material' *I*('inadequate quantity of material'; 'materials-related problems') equals 0.0519, which is the greatest MI amount amongst the first-level causes. The relationship between 'inadequate quantity of material' and the direct factor 'materials-related problems' is more dependent than the relationships between other first-level causes and 'materials-related problems', which can be characterised as almost independent relationships due to the small MI.

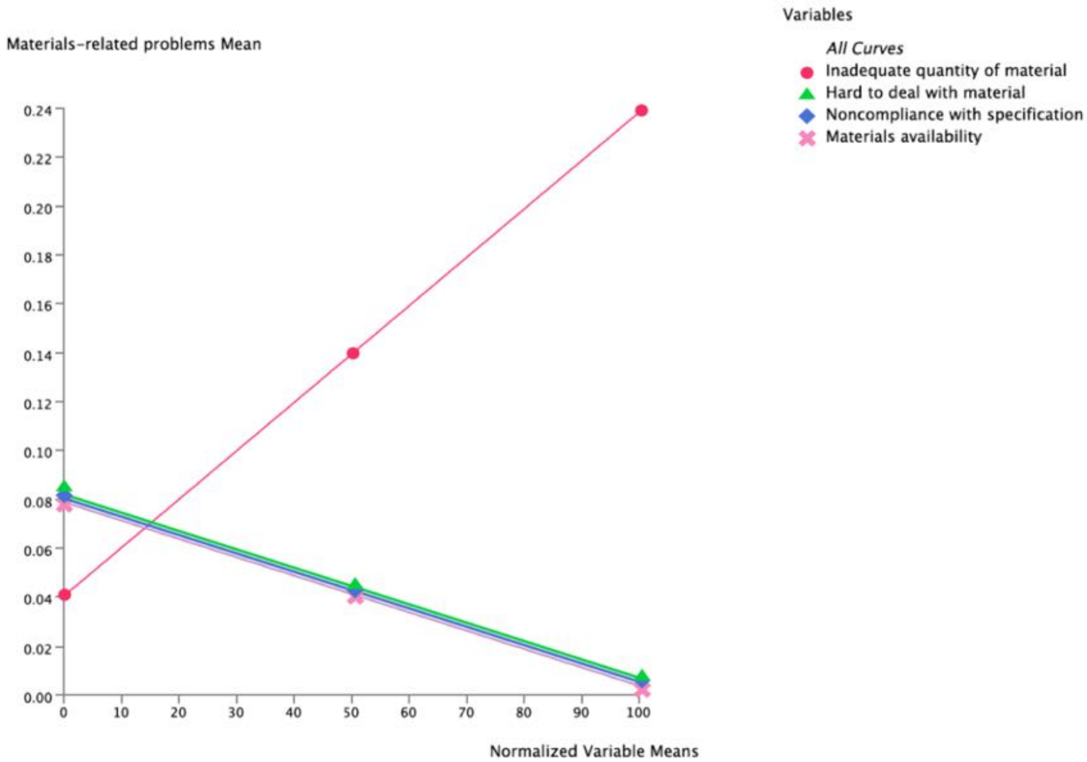


Figure 8.5 Direct effects of the potential causes of materials-related problems

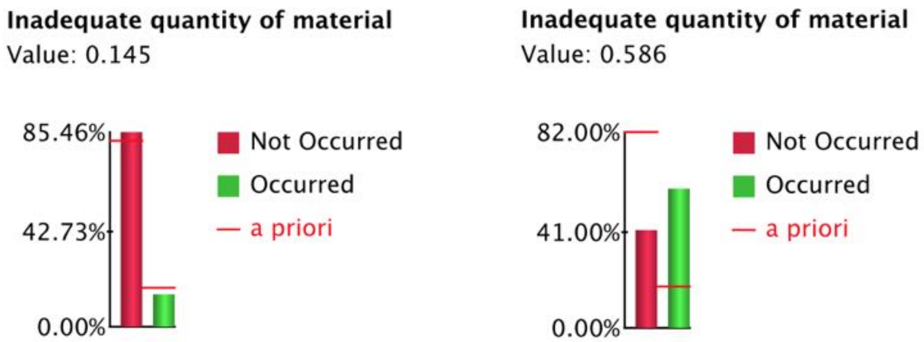
8.3.1.2.4 Maximal positive/negative variation

The maximal variation was determined for the significant first-level cause, namely, 'inadequate quantity of material'. The occurrence and non-occurrence of 'materials-related problems' in relation to occurrence and non-occurrence 'inadequate quantity of material' was analyzed. When there is non-occurrence of 'materials-related problems', the model predicts the probability of 'inadequate quantity of material' non-occurrence increases (as shown in the following table, Table 8.4).

Table 8.4 Maximal variation of the significant causes of materials-related problems

Node	*Priori Modal Value*		Modal Value		Maximal Variation	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Materials-related problems	**Scenario 1: *Not occurred***					
Inadequate quantity of material	*Not occurred*	*82.00%*	*Not occurred*	85.45%	3.455%	3.455%
Materials-related problems	**Scenario 2: *Occurred***					
Inadequate quantity of material	*Occurred*	*18.00%*	*Occurred*	58.60%	40.60%	40.60%

The maximal variation is 3.455% (negative variation) (as shown in Figure 8.6 (a)). In contrast, when there is occurrence of 'materials-related problems', the model predicts the probability of 'inadequate quantity of material' occurrence to increase. The maximal variation is 40.60% (positive variation) (as shown in Figure 8.6 (b)). 'Inadequate quantity of material' is the first-level cause most likely to underpin 'materials-related problems'.



(a) Materials-related problems: *Not occurred*

(b) Materials-related problems: *Occurred*

Figure 8.6 *Maximal variation* of inadequate quantity of material

8.3.1.3 First-level Causes of the Direct Factors 'Documentation-related underperformance'

8.3.1.3.1 Statistical examinationof the first-level

Table 8.5 provides prior probability values, before entering observations, and mean values of the first-level causes (i.e., 'specifications-related underperformance' and 'drawings-related underperformance') based on their own states for the direct factor 'documentation-related underperformance'. The independence tests *Chi–square* χ^2 shows significant associations between 'specifications-related underperformance' and ‘drawings-related underperformance’ and the direct factor ‘documentation-related underperformance’ at ; χ^2 (1) = 16.7342, (p<< 0.05), and; χ^2 (1) = 8.7882, (p< 0.05) respectively (as shown in Table 8.5). ‘Specifications-related underperformance’ and ‘drawings-related underperformance’ are each significantly associated with the direct factor ‘documentation-related underperformance’.

Table 8.5 Statistical analyses of the significant causes of documentation-related underperformance

Node	*Priori Modal Value*		Mean μ	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*						
Specifications-related underperformance	82.08%	17.92%	0.3213	16.734	1	0.0000	0.3465	0.0894
Drawings-related underperformance	67.87%	32.13%	0.1792	8.7882	1	0.0030	0.3061	0.0470

8.3.1.3.2 Direct Effect

The direct effect *De* of the first-level causes on the direct factor ‘documentation-related underperformance’ is listed in Table 8.5. ‘Specifications-related underperformance’ and ‘drawings-related underperformance’ were each found to have a high direct effect, at 0.3563 and 0.3146 respectively. Figure 8.7 shows the direct effect *De* of ‘documentation-related underperformance’ highlighting ‘specifications-related underperformance’ has a slightly higher *De* than ‘drawings-related underperformance’.

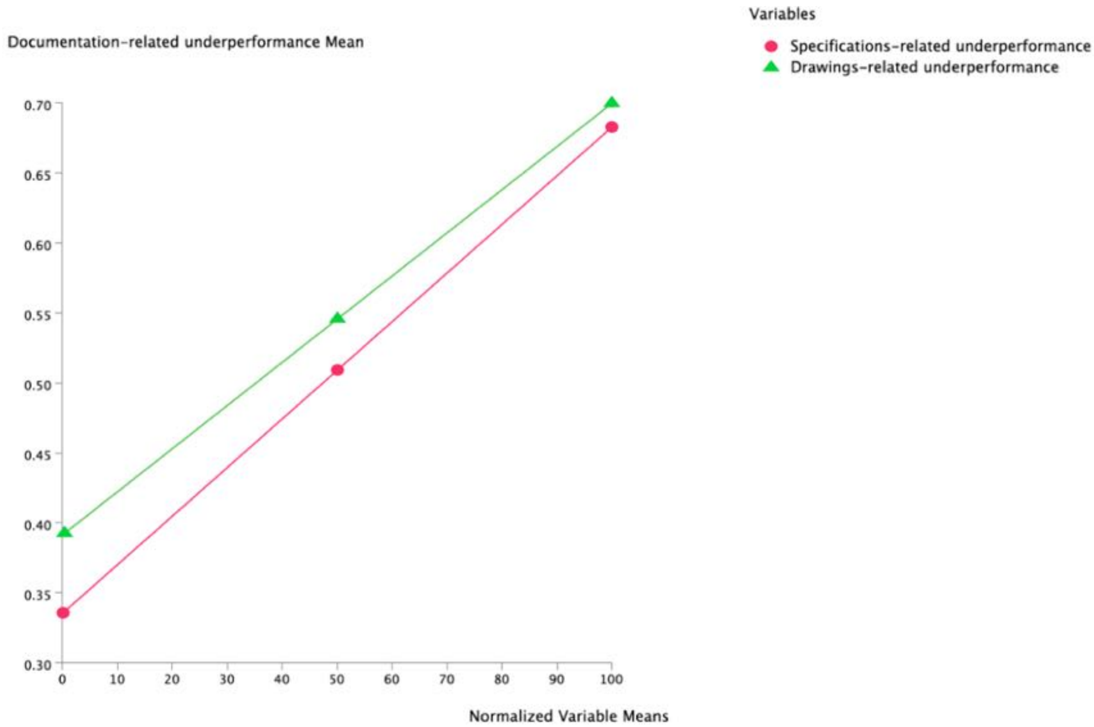


Figure 8.7 Direct effects of the potential causes of documentation-related underperformance

8.3.1.3.3 Mutual Information MI

Measurements of MI amount brought by first-level causes to the direct factor 'documentation-related underperformance' are listed in Table 8.5 and displayed in Figure 8.3. MI amount of the specifications was *I*('specifications-related underperformance'; 'documentation-related underperformance') = 0.0894, and for drawings *I*('drawings-related underperformance'; 'documentation-related underperformance') = 0.0470.

The MI between the 'specifications-related underperformance' with the direct factor 'documentation-related underperformance' is higher and the relationship between them more dependent than the MI and relationship between 'drawings-related underperformance' and the direct factor 'documentation-related underperformance'. Notwithstanding this, both 'specifications-related underperformance' and 'drawings-related underperformance' can be interpreted as having a dependent relationship with 'documentation-related underperformance'.

8.3.1.3.4 Maximal positive/negative variation

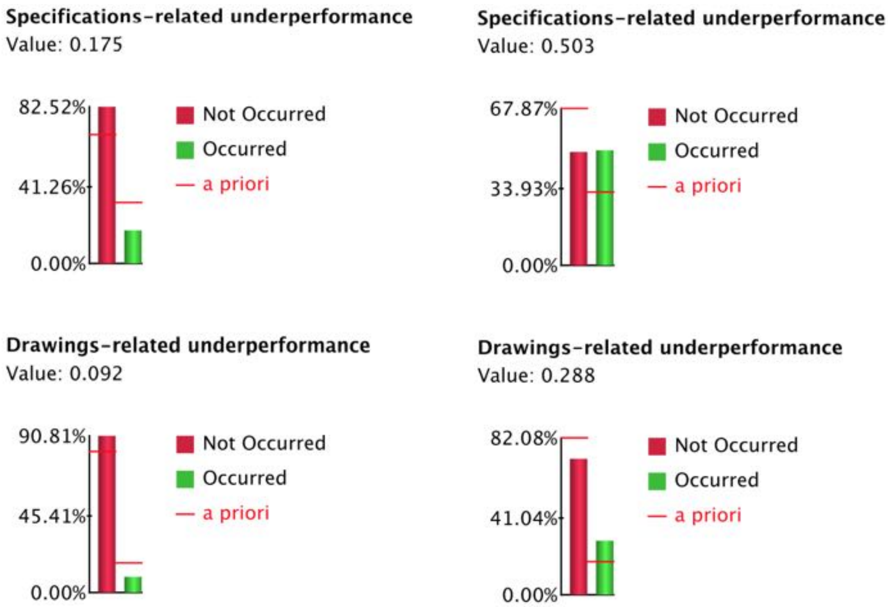
The maximal variation was determined for ‘specifications-related underperformance’ and ‘drawings-related underperformance’, each significant first-level causes. The occurrence and non-occurrence of ‘documentation-related underperformance’ in relation to occurrence and non-occurrence of ‘specifications-related underperformance’ and ‘drawings-related underperformance’, was analyzed.

When there is non-occurrence of ‘documentation-related underperformance’, the model predicts the probability of ‘specifications-related underperformance’ non-occurrence and the probability of ‘drawings-related underperformance’ non-occurrence each increase (as shown in the following table, Table 8.46). The maximal variation is 14.65% and 8.732% (negative variation) respectively (as shown in Figure 8.8 (a)).

Table 8.6 Maximal variation of the significant causes of documentation-related underperformance

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Documentation-related underperformance	**Scenario 1:** ***Not occurred***					
Specifications-related underperformance	*Not occurred*	*67.87%*	*Not occurred*	82.52%	14.65%	14.65%
Drawings-related underperformance	*Not occurred*	*82.08%*	*Not occurred*	90.81%	8.732%	8.732%
Documentation-related underperformance	**Scenario 2:** ***Occurred***					
Specifications-related underperformance	*Not occurred*	*32.13%*	*Occurred*	50.33%	18.19%	18.19%
Drawings-related underperformance	*Not occurred*	*17.92%*	*Occurred*	28.76%	10.84%	10.84%

In contrast, when there is occurrence of ‘documentation-related underperformance’, the model predicts that the probability of both ‘specifications-related underperformance’ and ‘drawings-related underperformance’ occurrence increases. The maximal variation is 18.19% and 10.84% (positive variation) respectively (as shown in Figure 8.8 (b)). ‘Specifications-related underperformance’ and ‘drawings-related underperformance’ material’ are first-level causes most likely to underpin ‘documentation-related underperformance’.



(a) Documentation-related underperformance: *Not occurred*

(b) Documentation-related underperformance: *Occurred*

Figure 8.8 *Maximal variation* of specifications & drawings-related underperformance

8.3.1.4 Second-level Causes of the First-level Cause 'Specifications-related Underperformance'

8.3.1.4.1 Statistical examination of the second-level causes

Table 8.7 provides prior probability values, before entering observations, and mean values of the second-level causes (i.e., 'missing information', 'misleading/clash information', 'wrong information' and 'unavailable documentations') based on their own states of the observed direct factor 'specifications-related underperformance'. The independence tests *Chi–square* χ^2 shows a significant association between second-level cause 'wrong information' and first-level cause 'specifications-related underperformance'; χ^2 (1) = 13.8518, (p< 0.05) (as shown in Table 8.7).

The independence tests *Chi–square* χ^2 for the remaining second-level causes failed to show a significant association with first-level causes 'specifications-related underperformance' (p> 0.05). 'Wrong information' is significantly associated with 'specifications-related underperformance'.

Table 8.7 Statistical analyses of the significant causes of specifications-related underperformance

Node	*Priori Modal Value*		Mean	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*	μ					
Wrong Information	92.59%	7.41%	0.0741	13.851	1	0.0002	0.5187	0.0740
Missing Information	96.30%	3.70%	0.0370	3.5714	1	0.0588	-0.2880	0.0191
Misleading/Clash information	99.26%	0.74%	0.0074	0.7204	1	0.3959	-0.2817	0.0038
Unavailable documentations	99.26%	0.74%	0.0074	0.7204	1	0.3959	-0.2817	0.0038

8.3.1.4.2 Direct Effect

The direct effect *De* of the second-level causes on the first-level cause 'specifications-related underperformance' is listed in Table 8.7. 'Wrong information' was found have highest direct effect, 0.5187. Figure 8.9 provides the direct effect *De* of the second-level causes and it clearly shows 'wrong information' as higher than the other causes.

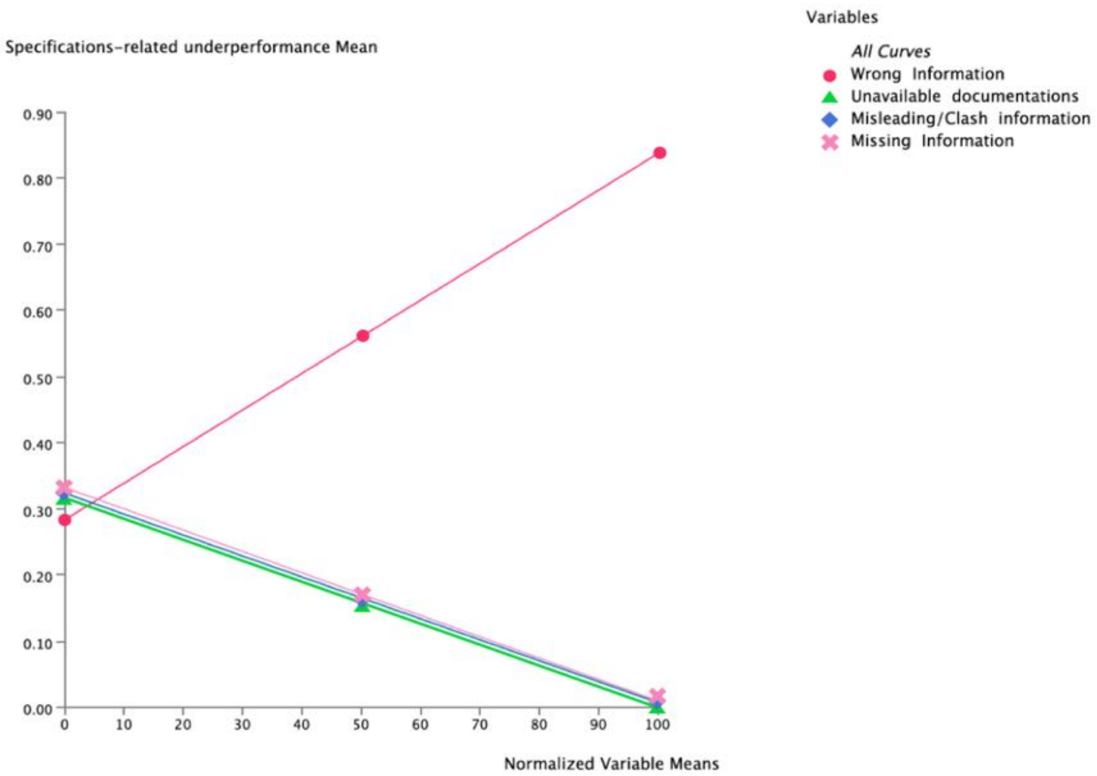


Figure 8.9 Direct effects of the potential causes of specifications-related underperformance

8.3.1.4.3 Mutual Information MI

Measurements of MI amount brought by second-level causes to the first-level causes 'specifications-related underperformance' are listed in Table 8.7 and displayed in Figure 8.3. MI amount of the 'wrong information' *I*('wrong information'; 'specifications-related underperformance') = 0.0740, which is the greatest MI amount amongst the second-level causes. The relationship between 'wrong information' and the first-level causes 'specifications-related underperformance' is more dependent than the relationships between other second-level causes and 'specifications-related underperformance', which can be characterised as almost independent relationships due to the small MI.

8.3.1.4.4 Maximal positive/negative variation

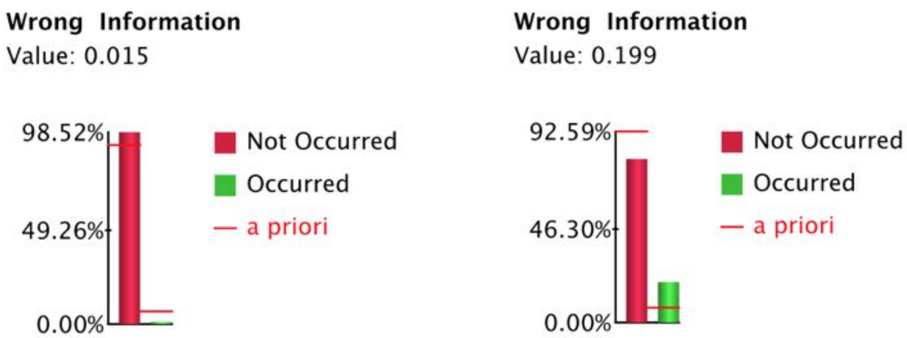
The maximal variation was determined for the significant second-level cause, namely, 'wrong information'. The occurrence and non-occurrence of 'specifications-related underperformance' in relation to occurrence and non-occurrence 'wrong information' was analyzed. When there is non-occurrence of 'specifications-related underperformance', the model predicts the probability of 'wrong information' non-occurrence increases (as shown in the following table, Table 8.8). The maximal variation is 5.9276% (negative variation) (as shown in Figure 8.10 (a)).

Table 8.8 Maximal variation of the significant causes of specifications-related underperformance

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Specifications-related underperformance	**Scenario 1:** ***Not occurred***					
Wrong Information	*Not occurred*	*92.59%*	*Not occurred*	98.52%	5.9276%	5.9276%
Specifications-related underperformance	**Scenario 2:** ***Occurred***					
Wrong Information	*Occurred*	*7.41%*	*Occurred*	19.93%	12.519%	12.519%

In contrast, when there is occurrence of 'specifications-related underperformance', the model predicts the probability of 'wrong information' occurrence to increase. The maximal variation is 12.5199% (positive variation) (as shown in Figure 8.10

(b)). ‘Wrong information’ is the second-level cause most likely to underpin ‘specifications-related underperformance’.



(a) Specifications-related underperformance: *Not occurred*

(b) Specifications-related underperformance: *Occurred*

Figure 8.10 *Maximal variation* of wrong information

8.3.1.5 Second-level Causes of the First-level Cause ‘Drawings-related Underperformance

8.3.1.5.1 Statistical examination of the second-level causes

Table 8.9 provides prior probability values, before entering observations, and mean values of the second-level causes (i.e., ‘missing information’, ‘misleading/clash information’, ‘wrong information’ and ‘unavailable documentations’) based on their own states of the observed direct factor ‘drawings-related underperformance’. The independence tests *Chi–square* χ^2 shows a significant association between second-level cause ‘wrong information’ and first-level cause ‘drawings-related underperformance’; χ^2 (1) = 24.2541, (p< 0.05) (as shown in Table 8.9).

The independence tests *Chi–square* χ^2 for the remaining second-level causes failed to show a significant association with the first-level causes ‘drawings-related underperformance’ (p> 0.05). ‘Wrong information’ is significantly associated with ‘drawings-related underperformance’.

Table 8.9 Statistical analyses of the significant causes of drawings-related underperformance

Node	*Priori Modal Value*		Mean μ	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*						
Wrong Information	92.59%	7.41%	0.0741	24.254	1	0.0001	0.6865	0.1296
Misleading/Clash information	99.26%	0.74%	0.0074	0.3407	1	0.5594	-0.1644	0.0018
Missing Information	99.26%	0.74%	0.0074	0.3407	1	0.5594	-0.1644	0.0018
Unavailable documentations	99.26%	0.74%	0.0074	0.3407	1	0.5594	-0.1644	0.0018

8.3.1.5.2 Direct Effect

The direct effect *De* of the second-level causes on the first-level cause 'drawings-related underperformance' is listed in Table 8.9. 'Wrong information' was found have highest direct effect, 0.6865. Figure 8.11 provides the direct effect *De* of the second-level causes and it clearly shows 'wrong information' as higher than the other causes.

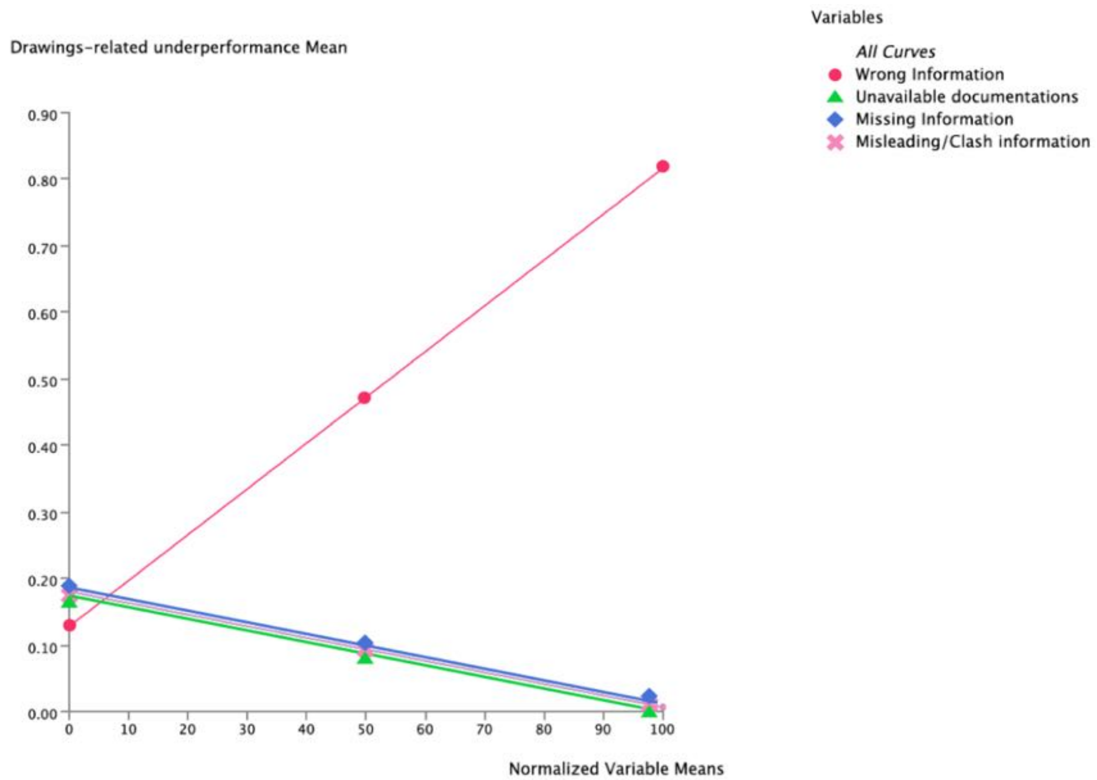


Figure 8.11 Direct effects of the potential causes of drawings-related underperformance

8.3.1.5.3 Mutual Information MI

Measurements of MI amount brought by second-level causes to the first-level causes 'drawings-related underperformance' are listed in Table 8.9 and displayed in Figure 8.3. MI amount of the 'wrong information' *I*('wrong information'; 'drawings-related underperformance') = 0.1296, which is the greatest MI amount amongst the second-level causes. The relationship between 'wrong information' and the first-level causes 'drawings-related underperformance' is more dependent than the relationships between other second-level causes and 'drawings-related underperformance', which can be characterised as almost independent relationships due to the small MI.

8.3.1.5.4 Maximal positive/negative variation

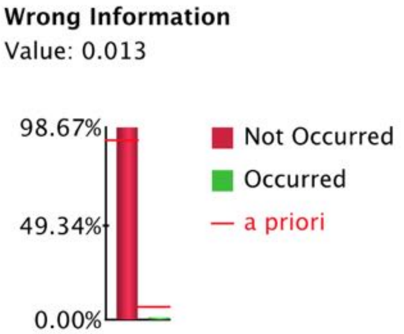
The maximal variation was determined for the significant second-level cause, namely, 'wrong information'. The occurrence and non-occurrence of 'drawings-related underperformance' in relation to occurrence and non-occurrence 'wrong information' was analyzed. When there is non-occurrence of 'drawings-related underperformance', the model predicts the probability of 'wrong information' non-occurrence increases (as shown in the following table, Table 8.10). The maximal variation is 6.0799% (negative variation) (as shown in Figure 8.12 (a)).

Table 8.10 Maximal variation of the significant causes of drawings-related underperformance

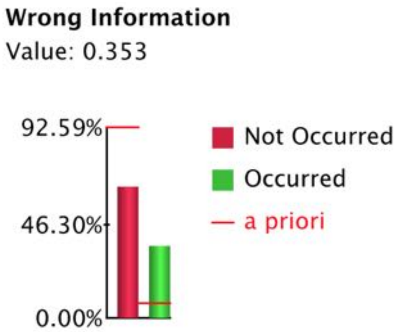
Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Drawings-related underperformance	**Scenario 1:** ***Not occurred***					
Wrong Information	*Not occurred*	*92.59%*	*Not occurred*	98.67%	6.0799%	6.0799%
Drawings-related underperformance	**Scenario 2:** ***Not occurred***					
Wrong Information	*Occurred*	*7.41%*	*Occurred*	35.25%	27.8467%	27.8467%

In contrast, when there is occurrence of 'drawings-related underperformance', the model predicts the probability of 'wrong information' occurrence to increase. The maximal variation is 27.8467% (positive variation) (as shown in Figure 8.12 (b)).

‘Wrong information’ is the second-level cause most likely to underpin ‘drawings-related underperformance’.



(a) Drawings-related underperformance:
Not occurred



(b) Drawings-related underperformance:
Occurred

Figure 8.12 *Maximal variation* of wrong information

8.3.1.6 First-level Causes of the Direct Factors ‘Supervisor-related Underperformance’

8.3.1.6.1 Statistical examinationof the first-level causes

Table 8.11 provides prior probability values, before entering observations, and mean values of the first-level causes (i.e., ‘lack of knowledge’, ‘lack of commitment’, ‘lack of experience’ and ‘lack of skills’) based on their own states of the observed direct factor ‘supervisor-related underperformance’. The independence tests *Chi–square* χ^2 shows a significant association between first-level cause ‘lack of commitment’ and direct factor ‘supervisor-related underperformance’; χ^2 (1) = 8.7623, (p< 0.05) (as shown in Table 8.11).

The independence tests *Chi–square* χ^2 for the remaining first-level causes failed to show a significant association with direct factor ‘supervisor-related underperformance’ (p>> 0.05). ‘Lack of commitment’ is significantly associated with ‘supervisor-related underperformance’.

Table 8.11 Statistical analyses of the significant causes of supervisor-related underperformance

Node	*Priori Modal State and Value*			Mean μ	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*							
Lack of commitment	72.38%	27.62%		0.2762	8.7623	1	0.0030	0.1665	0.0468
Lack of skills	54.87%	45.13%		0.4513	0.4888	1	0.4844	0.0331	0.0026
Lack of knowledge	57.23%	42.27%		0.4277	0.2747	1	0.6001	-0.0248	0.0015
	Low	**Medium**	**High**						
Lack of experience	84.34%	14.67%	0.99%	0.1665	2.8711	2	0.2379	-0.0804	0.0153

8.3.1.6.2 Direct Effect

The direct effect *De* of the first-level causes on direct factor ‘supervisor-related underperformance’ is listed in Table 8.11. ‘Lack of commitment’ was found have highest direct effect, 0.1665. Figure 8.13 provides the direct effect *De* of the first-level causes and it clearly shows ‘lack of commitment’ as higher than the other causes.

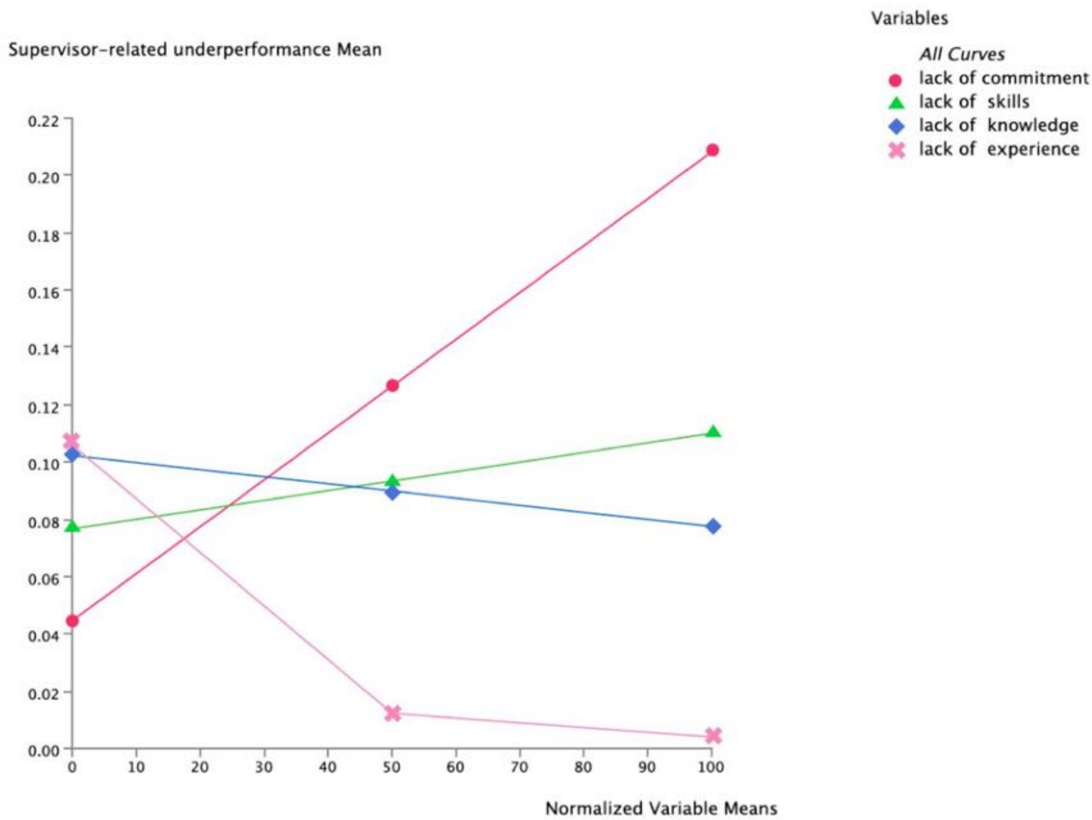


Figure 8.13 Direct effects of the potential causes of supervisor-related underperformance

8.3.1.6.3 Mutual Information MI

Measurements of MI amount brought by first-level causes to the direct factor 'supervisor-related underperformance' are listed in Table 8.11 and displayed in Figure 8.3. MI amount of the 'lack of commitment' *I*('lack of commitment'; 'supervisor-related underperformance') equals 0.0468, which is the greatest MI amount amongst the first-level causes. The relationship between 'lack of commitment' and the direct factor 'supervisor-related underperformance' is more dependent than the relationships between other first-level causes and 'supervisor-related underperformance', which can be characterised as almost independent relationships due to the small MI.

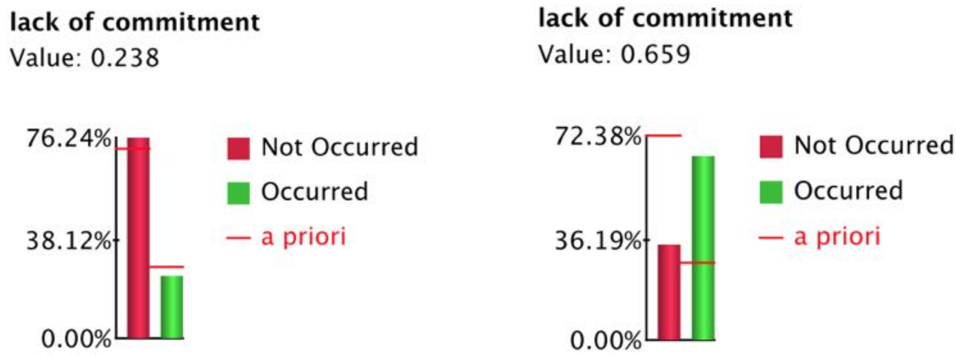
8.3.1.6.4 Maximal positive/negative variation

The maximal variation was determined for the significant first-level cause, namely, 'lack of commitment'. The occurrence and non-occurrence of 'supervisor-related underperformance' in relation to occurrence and non-occurrence 'lack of commitment' was analyzed. When there is non-occurrence of 'lack of commitment', the model predicts the probability of 'lack of commitment' non-occurrence increases (as shown in the following table, Table 8.12). The maximal variation is 3.861% (negative variation) (as shown in Figure 8.14 (a)).

Table 8.12 Maximal variation of the significant causes of supervisor-related underperformance

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Supervisor-related underperformance	**Scenario 1: *Not occurred***					
Lack of commitment	*Not occurred*	*72.37%*	*Not occurred*	76.23%	3.861%	3.861%
Supervisor-related underperformance	**Scenario 2: *Occurred***					
Lack of commitment	*Not occurred*	*27.62%*	*Occurred*	65.86%	38.24%	38.24%

In contrast, when there is occurrence of ‘supervisor-related underperformance’, the model predicts the probability of ‘lack of commitment’ occurrence to increase. The maximal variation is 38.24% (positive variation) (as shown in Figure 8.14 (b)). ‘Lack of commitment’ is the first-level cause most likely to underpin ‘supervisor-related underperformance’.



(a) Supervisor-related underperformance: *Not occurred*

(b) Supervisor-related underperformance: *Occurred*

Figure 8.14 *Maximal variation* of lack of commitment

8.3.1.7 Second-level Causes of the First-level Causes ‘Lack of Commitment’

8.3.1.7.1 Statistical examination of the second-level causes

Table 8.13 provides prior probability values, before entering observations, and mean values of the second-level causes (i.e., ‘communication with worker’, ‘adherence to procedures’, ‘adherence to design & standard (SBC)’ and ‘absenteeism’) based on their own states of the observed first-level cause ‘lack of commitment’. The independence tests *Chi–square* χ^2 shows a significant association between second-level cause ‘absenteeism’ and ‘communication with worker’ and first-level cause ‘lack of commitment’; χ^2 (1) = 19.9836, (p< 0.05), and χ^2 (1) = 9.7540, (p< 0.05) respectively (as shown in Table 8.13).

The independence tests *Chi–square* χ^2 for the remaining second-level causes failed to show a significant association with first-level cause ‘lack of commitment’ (p> 0.05). ‘Absenteeism’ and ‘communication with worker’ are significantly associated with ‘lack of commitment’.

Table 8.13 Statistical analyses of the significant causes lack of commitment

Node	*Priori Modal Value*		Mean μ	χ^2	*df*	p-value	Direct Effect	MI
	Not Occurred	*Occurred*						
Absenteeism	70.37%	29.63%	0.4444	1.2210	1	0.2691	-0.0798	0.0065
Communication with worker	88.89%	11.11%	0.2963	19.983	1	0.0000	0.3639	0.1068
Adherence to procedures	92.59%	7.41%	0.1111	9.7540	1	0.0017	-0.2886	0.0521
Adherence to design & standard (SBC)	55.56%	44.44%	0.0741	6.3418	1	0.1179	-0.2771	0.0339

8.3.1.7.2 Direct Effect

The direct effect *De* of the second-level causes on the first-level cause 'lack of commitment' is listed in Table 8.13. 'Absenteeism' was found have highest direct effect, 0.3639. Figure 8.15 provides the direct effect *De* of the second-level causes and it clearly shows 'absenteeism' as higher than the other causes.

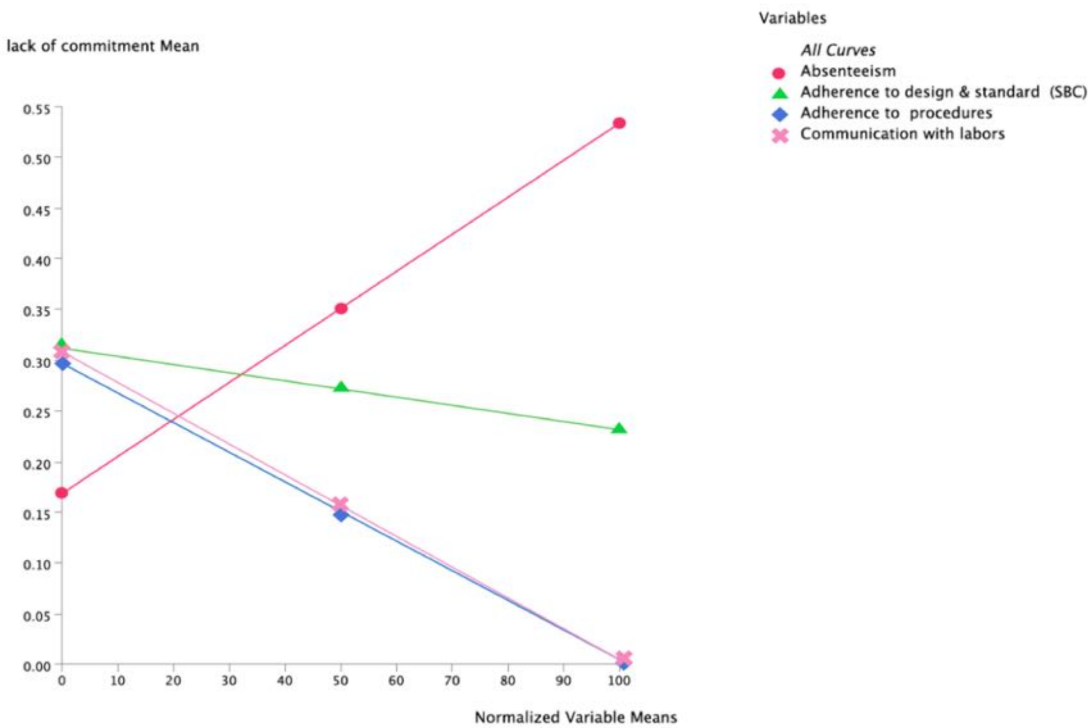


Figure 8.15 Direct effects for the potential causes of lack of commitment

8.3.1.7.3 Mutual Information MI

Measurements of MI amount brought by second-level causes to the first-level causes 'lack of commitment' are listed in Table 8.13 and displayed in Figure 8.3. MI amount of the 'absenteeism' *I*('absenteeism'; 'lack of commitment') = 0.1068, which is the greatest MI amount amongst the second-level causes. The relationship between 'absenteeism' and the first-level causes 'lack of commitment' is more dependent than the relationships between other second-level causes and 'lack of commitment', which can be characterised as almost independent relationships due to the small MI.

8.3.1.7.4 Maximal positive/negative variation

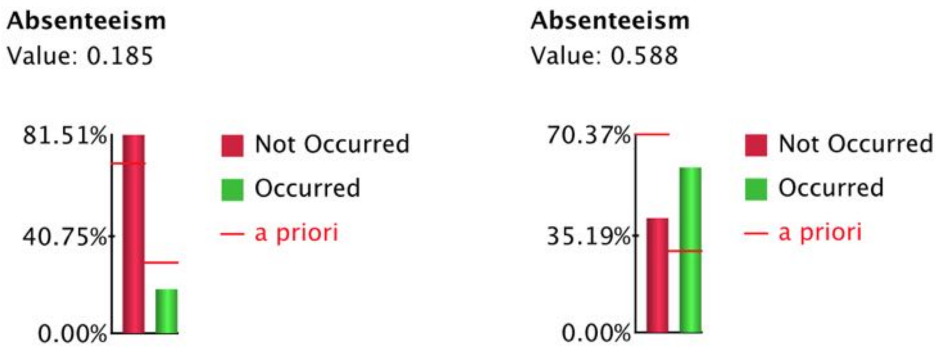
The maximal variation was determined for the significant second-level cause, namely, 'absenteeism'. The occurrence and non-occurrence of 'lack of commitment' in relation to occurrence and non-occurrence 'absenteeism' was analyzed.

When there is non-occurrence of 'lack of commitment', the model predicts the probability of 'absenteeism' non-occurrence increases (as shown in the following table, Table 8.14). The maximal variation is 11.13% (negative variation) (as shown in Figure 8.16 (a)).

Table 8.14 Maximal variation of the significant causes lack of commitment

Node	***Priori Modal Value***		**Modal Value**		**Maximal Variation**	
	State	*%*	*State*	*%*	**Positive**	**Negative**
Lack of commitment	**Scenario 1:** ***Not occurred***					
Absenteeism	*Not occurred*	*70.37%*	*Not occurred*	81.50%	11.13%	11.13%
Lack of commitment	**Scenario 2:** ***Occurred***					
Absenteeism	*Occurred*	*29.63%*	*Occurred*	58.81%	29.18%	29.18%

In contrast, when there is occurrence of 'lack of commitment', the model predicts the probability of 'absenteeism' occurrence to increase. The maximal variation is 29.18% (positive variation) (as shown in Figure 8.16 (b)). 'Absenteeism' is the second-level cause most likely to underpin 'lack of commitment'.



(a) Lack of commitment: *Not occurred*

(b) Lack of commitment: *Occurred*

Figure 8.16 *Maximal variation* of absenteeism

8.3.2 STR.5

The results for STR.5 were generated and interpreted as per the method applied to STR.1. Table 8.15 presents the prior probability values, mean values, direct effect, mutual information (MI) and maximal variation for all significant variables.

8.3.2.1 Direct Factors with STR.5

The independence tests *Chi–square* χ^2 show a significant association between 'equipment-related problems' and 'worker-related underperformance' with the STR.5; χ^2 (2) = 9.446, (p< 0.05), and; χ^2 (2) = 19.77, (p< 0.05) respectively (as shown in Table 8.15). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association (p> 0.05). The results support that only 'equipment-related problems' and 'worker-related underperformance' are significantly associated with STR.5 performance.

'Equipment-related problems' and 'worker-related underperformance' were found have highest direct effect on the target node STR.5, at 0.245 and 0.102 respectively (as shown in Figure 8.18). Also, MI amount of information brought by the direct factors to the target variable STR.5 was I('equipment-related problems'; 'STR.5') = 0.0185, and I('worker-related underperformance'; 'STR.5') = 0.0335 (as shown in Table 8.15 and Figure 8.17). 'Equipment-related problems' and 'worker-related underperformance' have the highest MI with STR.5 indicating a more dependent relationship between these direct factors and the target variable.

Table 8.15 Statistical analyses of the significant causes of STR.5

Node	*Priori Modal Value*		Mean	χ^2	*df*	p-value	Direct Effect	MI	Modal Value		Maximal Variation	
	Not Occurred	*Occurred*	μ						*State*	*%*	Positive	Negative
STR.5	**Scenario 1: Defective-work**											
Equipment-related problems	53.29%	46.71%	0.4671	9.446	2	0.0089	0.245	0.0185	*Occurred*	57.21%	10.49%	10.49%
Worker-related underperformance	14.71%	85.29%	0.8529	19.77	2	0.0001	0.102	0.0335	*Occurred*	92.34%	7.05%	7.05%
STR.5	**Scenario 2: Acceptable-work**											
Worker-related underperformance	14.71%	85.29%	0.8529	19.77	2	0.0001	0.102	0.0335	*Not Occurred*	75.43%	9.855%	9.855%
Equipment-related problems	53.29%	46.71%	0.4671	9.446	2	0.0089	0.245	0.0185	*Not Occurred*	56.34%	3.053%	3.053%
STR.5	**Scenario 3: Perfect-work**											
Worker-related underperformance	14.71%	85.29%	0.8529	19.77	2	0.0001	0.102	0.0335	*Not Occurred*	89.88%	4.597%	4.597%
Equipment-related problems	53.29%	46.71%	0.4671	9.446	2	0.0089	0.245	0.0185	*Occurred*	62.18%	8.899%	8.899%
Equipment-related problems	**Scenario 1: Not Occurred**											
Hard to deal with equipment	55.55%	44.44%	0.4444	185.48	1	0.0000	0.070	0.0037	*Not Occurred*	58.89%	3.331%	3.331%
Equipment-related problems	**Scenario 2: Occurred**											
Hard to deal with equipment	55.55%	44.44%	0.4444	185.48	1	0.0000	0.070	0.0037	*Occurred*	48.24%	3.799%	3.799%
Worker-related underperformance	**Scenario 1: Not Occurred**											
Lack of commitment	65.50	34.50	0.3450	4.115	1	0.0424	0.137	0.0308	*Not Occurred*	87.52%	22.02%	22.02%
Lack of skills	46.40	53.60	0.5360	62.79	1	0.0000	0.089	0.0126	*Not Occurred*	62.27%	15.87%	15.87%
Worker-related underperformance	**Scenario 2: Occurred**											
Lack of commitment	65.50	34.50	0.3450	4.115	1	0.0424	0.137	0.0308	*Occurred*	61.71%	3.797%	3.797%
Lack of skills	46.40	53.60	0.5360	62.79	1	0.0000	0.089	0.0126	*Occurred*	56.33%	2.737%	2.737%
Lack of commitment	**Scenario 1: Not Occurred**											
Adherence to design & standard (SBC)	81.48	18.52	0.1852	34.94	1	0.0000	0.610	0.1867	*Not Occurred*	95.91%	14.43%	14.43%
Adherence to procedures	96.30	3.70	0.0370	10.36	1	0.0013	0.652	0.0553	*Not Occurred*	99.94%	3.645%	3.645%
Lack of commitment	**Scenario 2: Occurred**											
Adherence to design & standard (SBC)	81.48	18.52	0.1852	34.94	1	0.0000	0.610	0.1867	*Occurred*	45.92%	27.41%	27.41%
Adherence to procedures	96.30	3.70	0.0370	10.36	1	0.0013	0.652	0.0553	*Occurred*	10.62%	6.921%	6.921%
Lack of skills	**Scenario 1Not Occurred**											
Work Accurately	62.96	37.04	0.3704	11.43	1	0.0007	0.292	0.0611	*Not Occurred*	77.86%	14.90%	14.90%
Handle with material/equipment	92.59	7.41	0.0741	10.43	1	0.0012	0.461	0.0558	*Not Occurred*	99.51%	6.920%	6.920%
Lack of skills	**Scenario 2: Occurred**											
Work Accurately	62.96	37.04	0.3704	11.43	1	0.0007	0.292	0.0611	*Occurred*	49.94%	12.90%	12.90%
Handle with material/equipment	92.59	7.41	0.0741	10.43	1	0.0012	0.461	0.0558	*Occurred*	13.40%	5.992%	5.992%

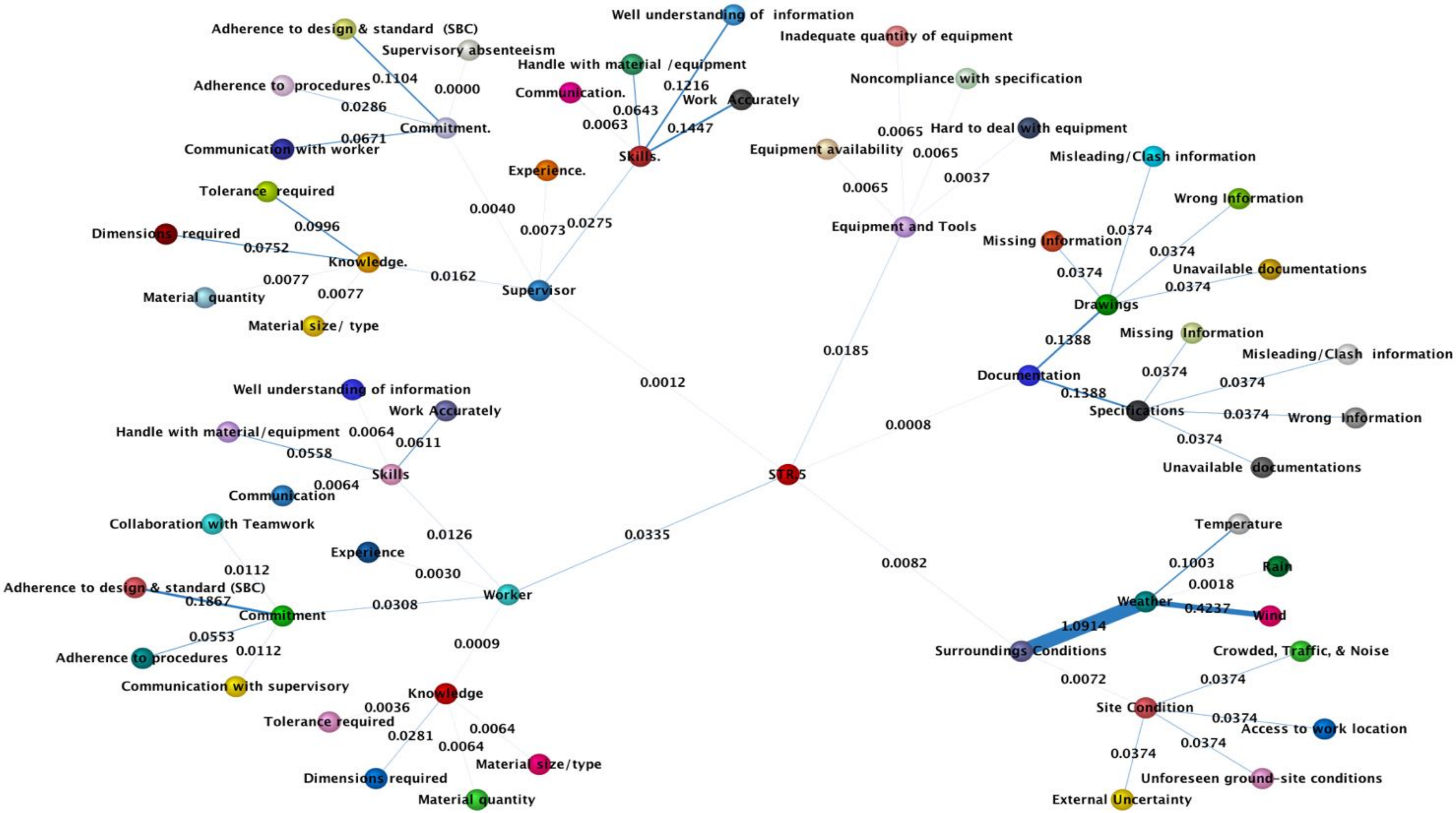


Figure 8.17 MI of STR.5 network

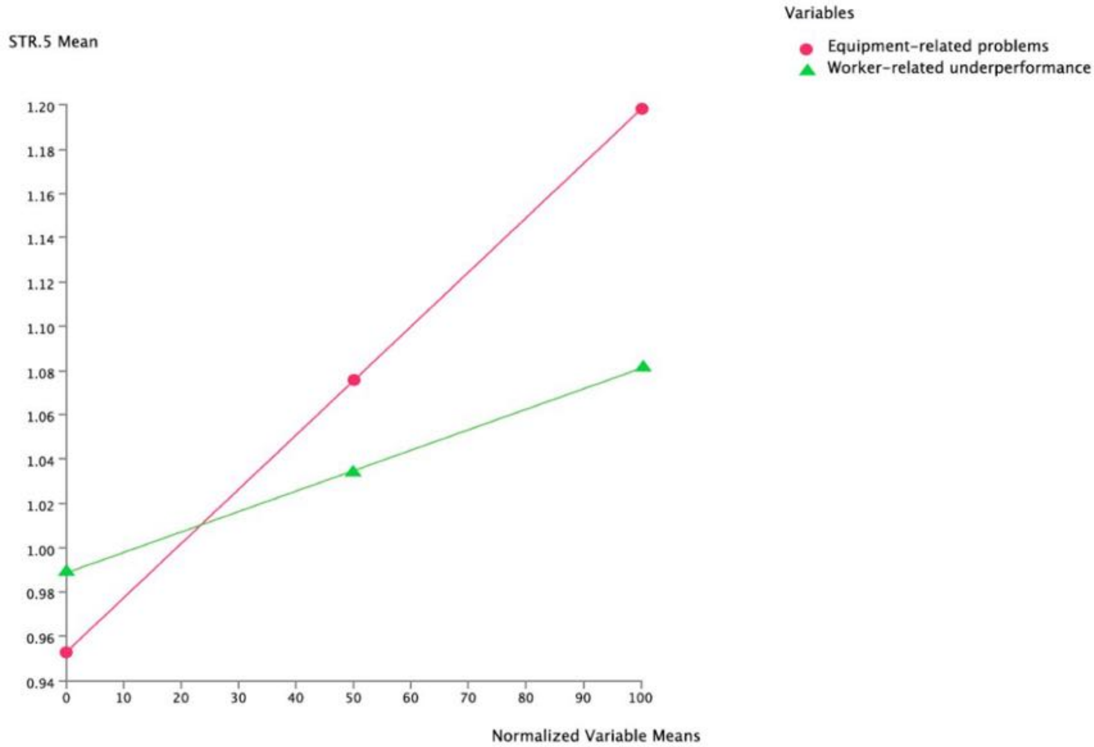


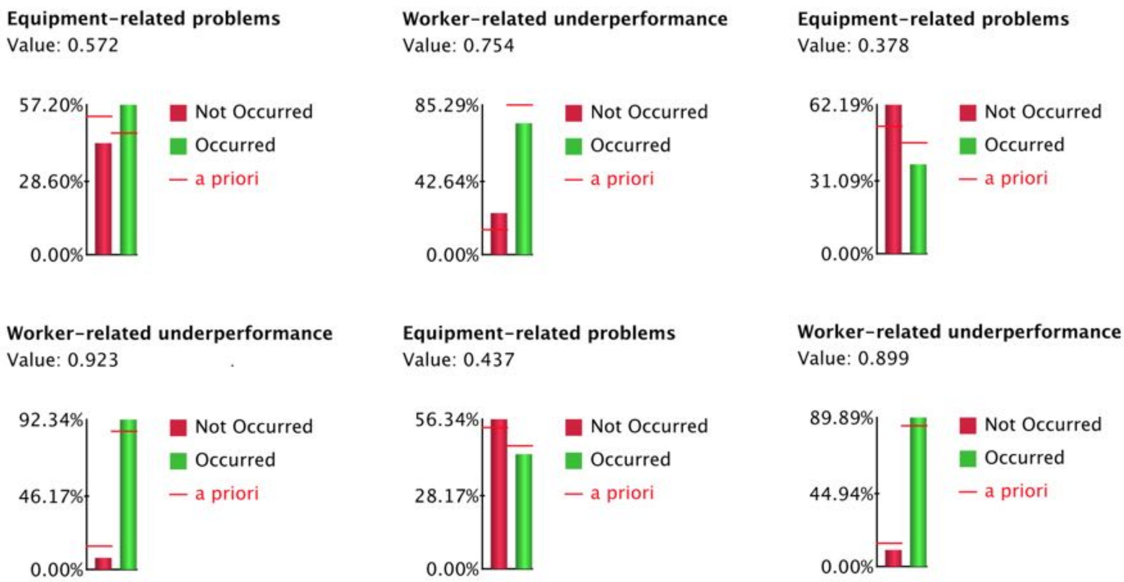
Figure 8.18 Direct effects of the potential causes of STR.5

The maximal variation of the significant direct factors, namely, 'equipment-related problems' and 'worker-related underperformance', as shown in the previous tests: the *Chi–square* χ^2 test, direct effect and the mutual information MI was calculated.

Performance of STR.5 could be 'perfect-work', 'acceptable-work' or 'defective-work'. When 'defective-work' was observed (i.e., the state of the quality output for executing STR.5 is defective-work), the model predicted that the probability of 'equipment-related problems' and 'worker-related underperformance' occurrence increased. The maximal variation was 10.49% and 7.05% respectively (positive variation) (as shown in Table 8.15 and Figure 8.19 (a)). 'Equipment-related problems' and 'worker-related underperformance' are direct factors most prone to cause 'defective-work' in relation to STR.5.

When 'acceptable-work' was observed (i.e., the state of the quality output for executing STR.5 is acceptable-work), the model predicted that the probability of 'equipment-related problems' and 'worker-related underperformance' occurrence decreased. The maximal variation was 3.053% and 9.855% (negative variation) respectively (as shown in Table 8.15 and Figure 8.19 (b)). 'Equipment-related problems' and 'worker-related underperformance' are direct factors less prone to cause 'acceptable-work'.

Similarly, when 'perfect-work' was observed (i.e., the state of the quality output for executing STR.5 is perfect-work), the model predicted that the probability of 'equipment-related problems' non-occurrence increased (negative variation), and 'worker-related underperformance' occurrence increased (positive variation). The maximal variation was 8.899% and 4.597% respectively (as shown in Table 8.15 and Figure 8.19 (c)). 'Equipment-related problems' is direct factor less prone to cause 'perfect-work' and 'worker-related underperformance' is direct factors somewhat prone to cause 'perfect-work'.



(a) Defective-work (b) Acceptable-work (c) Perfect-work

Figure 8.19 *Maximal variation* of the direct factors of STR.5

8.3.2.2 First-level Causes of the Direct Factors 'Equipment-related Problems'

The independence tests *Chi–square* χ^2 show a significant association between 'hard to deal with equipment' with the 'equipment-related problems'; χ^2 (1) = 185.48, ($p<$ 0.05) (as shown in Table 8.15). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p>$ 0.05). The results support that only ‘hard to deal with equipment’ is significantly associated with ‘equipment-related problems’.

‘Hard to deal with equipment’ was found has highest direct effect on direct factor ‘equipment-related problems’, at 0.070 (as shown in Figure 8.20). MI amount of information brought by first-level causes ‘hard to deal with equipment’ to direct factor ‘equipment-related problems’ was *I*(‘hard to deal with equipment’; ‘equipment-related problems’) = 0.0037 (as shown in Table 8.15 and Figure 8.17). MI value between ‘Hard to deal with equipment’ and ‘equipment-related problems’ indicates a somewhat dependent relationship between the first-level causes and the direct factor.

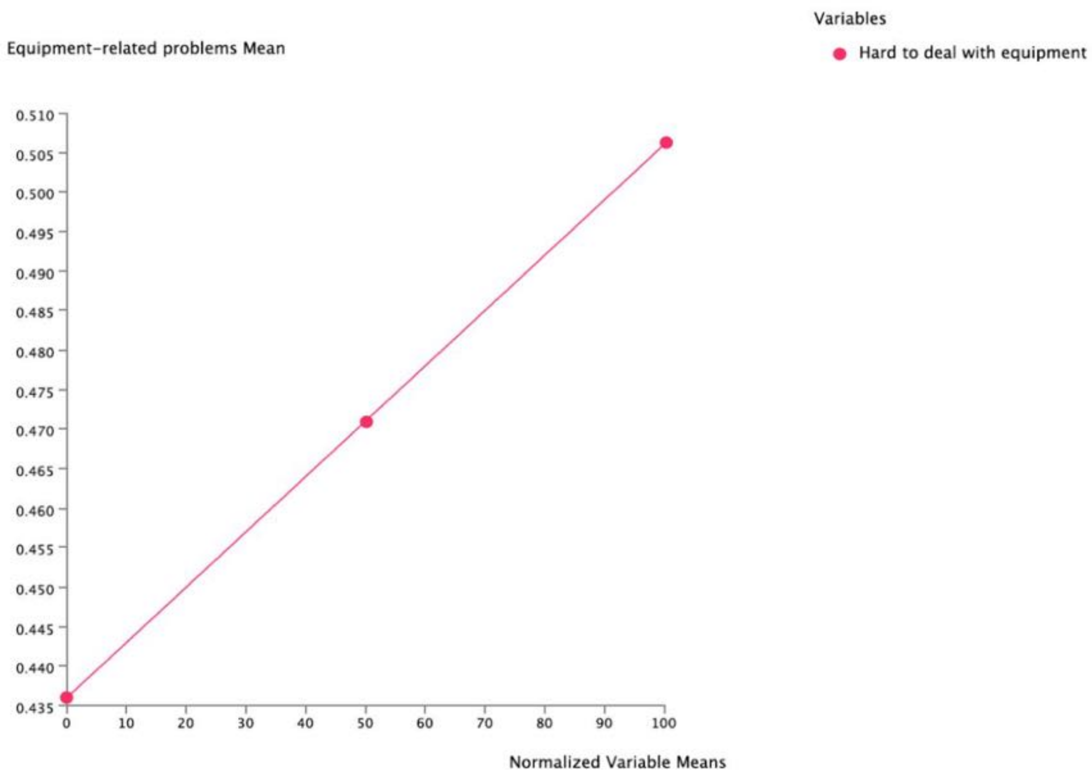
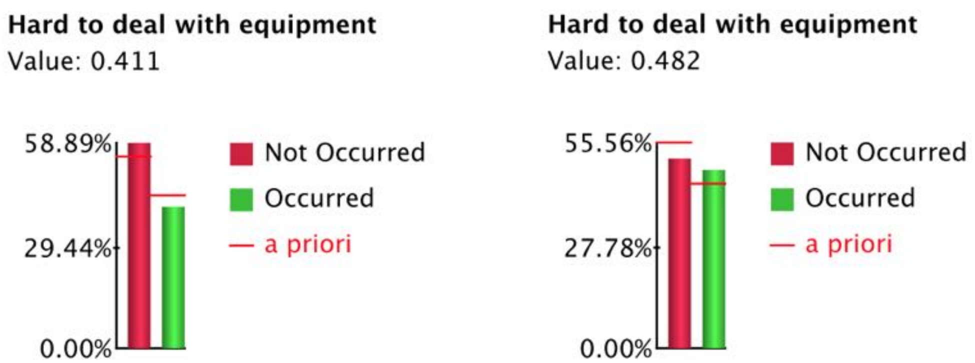


Figure 8.20 Direct effects of the potential causes of equipment-related problems

The maximal variation was determined for the significant first-level cause, namely, ‘hard to deal with equipment’. The occurrence and non-occurrence of ‘equipment-related problems’ in relation to occurrence and non-occurrence ‘hard to deal with equipment’ was analyzed. When there is non-occurrence of ‘equipment-related problems’, the model predicts the probability of ‘hard to deal with equipment’ non-occurrence increases (as shown in Table 8.15). The maximal variation is 3.331%

(negative variation) (as shown in Figure 8.21 (a)). In contrast, when there is occurrence of ‘equipment-related problems’, the model predicts the probability of ‘hard to deal with equipment’ occurrence to increase. The maximal variation is 3.799% (positive variation) (as shown in Figure 8.21 (b)). ‘Hard to deal with equipment’ is the first-level cause most likely to underpin ‘equipment-related problems’.



(a) Equipment-related problems: *Not occurred*

(b) Equipment-related problems: *Occurred*

Figure 8.21 *Maximal variation* of hard to deal with equipment

8.3.2.3 First-level Causes of the Direct Factors ‘Worker-related underperformance’

The independence tests *Chi–square* χ^2 show a significant association between ‘lack of commitment’ and ‘lack of skills’ with the ‘worker-related underperformance’; χ^2 (1) = 4.115, ($p< 0.05$), and χ^2 (1) = 62.79, ($p< 0.05$) respectively (as shown in Table 8.15). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p> 0.05$). The results support that only ‘lack of commitment’ and ‘lack of skills’ is significantly associated with ‘worker-related underperformance’.

‘Lack of commitment’ and ‘lack of skills’ were found have highest direct effect on direct factor ‘worker-related underperformance’, at 0.137 and 0.089 (as shown in Figure 8.22). Also, MI amount of information brought by first-level causes ‘lack of commitment’ and ‘lack of skills’ to direct factor ‘worker-related underperformance’ were *I*(‘lack of commitment’; ‘worker-related underperformance’) = 0.0308 and

I(‘lack of skills’; ‘worker-related underperformance’) = 0.0126 (as shown in Table 8.15 and Figure 8.17). ‘Lack of commitment’ and ‘lack of skills’ have the highest MI with ‘worker-related underperformance’ indicating a more dependent relationship between the first-level causes and the direct factor.

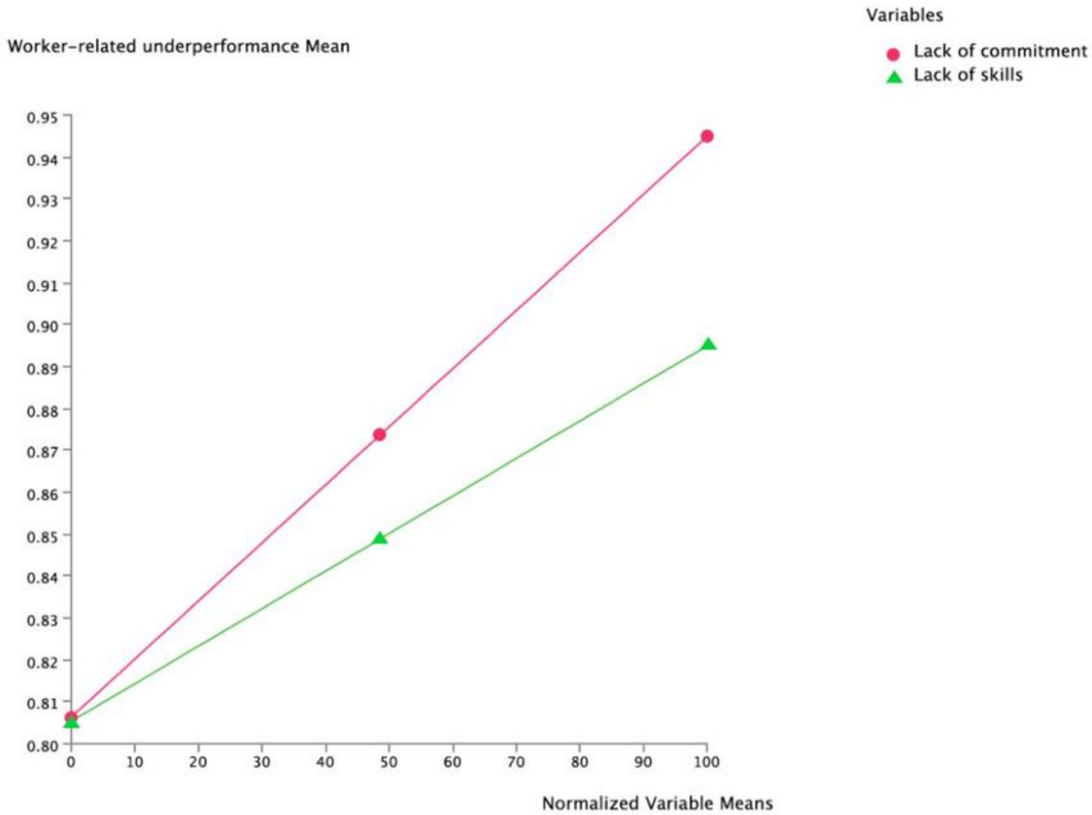
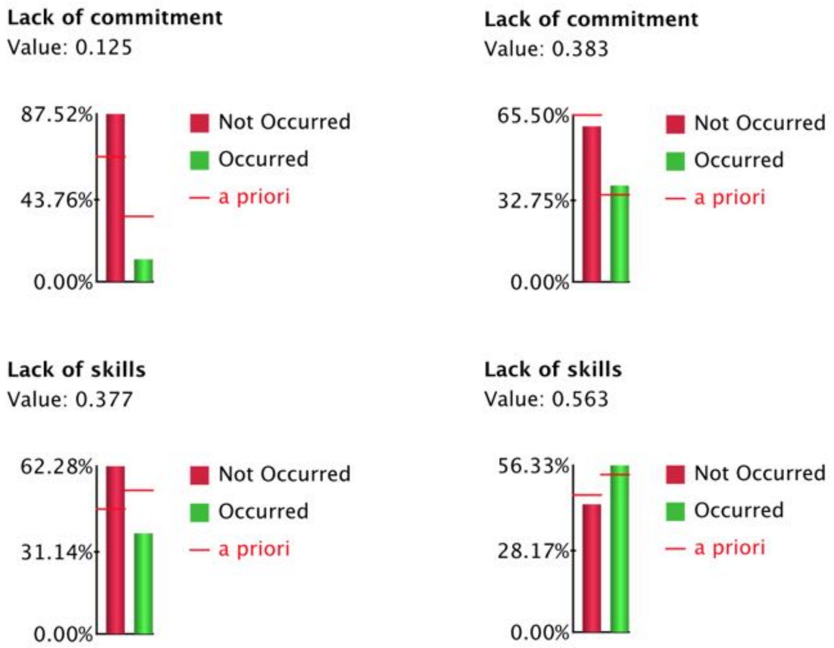


Figure 8.22 Direct effects of the potential causes of worker-related underperformance

The maximal variation was determined for the significant first-level cause, namely, ‘lack of commitment’ and ‘lack of skills’. The occurrence and non-occurrence of ‘worker-related underperformance’ in relation to occurrence and non-occurrence ‘lack of commitment’ and ‘lack of skills’ were analyzed. When there is non-occurrence of ‘worker-related underperformance’, the model predicts the probability of ‘lack of commitment’ and ‘lack of skills’ non-occurrence increases (as shown in Table 8.15). The maximal variation is 22.02% and 15.87% (negative variation) respectively (as shown in Figure 8.23 (a)).

In contrast, when there is occurrence of ‘worker-related underperformance’, the model predicts the probability of ‘lack of commitment’ and ‘lack of skills’ occurrence to increase. The maximal variation is 3.797% and 2.737% (positive variation) respectively (as shown in Figure 8.23 (b)). ‘‘Lack of commitment’ and ‘lack of skills’ are the first-level causes most likely to underpin ‘worker-related underperformance’.



(a) Worker-related underperformance: *Not occurred* (b) Worker-related underperformance: *Occurred*

Figure 8.23 *Maximal variation* of lack of commitment & skills

8.3.2.4 Second-level Causes of the First-level Cause ‘Lack of Commitment’

The independence tests *Chi–square* χ^2 show a significant association between ‘adherence to design & standard SBC’ and ‘adherence to procedures’ with the ‘lack of commitment’; χ^2 (1) = 34.94, (p< 0.05), and χ^2 (1) = 10.36, (p< 0.05) respectively (as shown in Table 8.15). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association (p> 0.05). The results support that only ‘adherence to design & standard’ and ‘adherence to procedures’ is significantly associated with ‘lack of commitment’.

‘Adherence to design & standard’ and ‘adherence to procedures’ were found have highest direct effect on first-level causes ‘lack of commitment’, at 0.610 and 0.652 (as shown in Figure 8.24). Also, MI amount of information brought by second-level causes ‘adherence to design & standard’ and ‘adherence to procedures’ to first-level causes 'lack of commitment' were I('adherence to design & standard'; 'lack of commitment') = 0.1867 and I('adherence to procedures'; 'lack of commitment') = 0.0553 (as shown in Table 8.15 and Figure 8.17). 'Adherence to design & standard' and 'adherence to procedures' have the highest MI with 'lack of commitment' indicating a more dependent relationship between the second-level causes and the first-level causes.

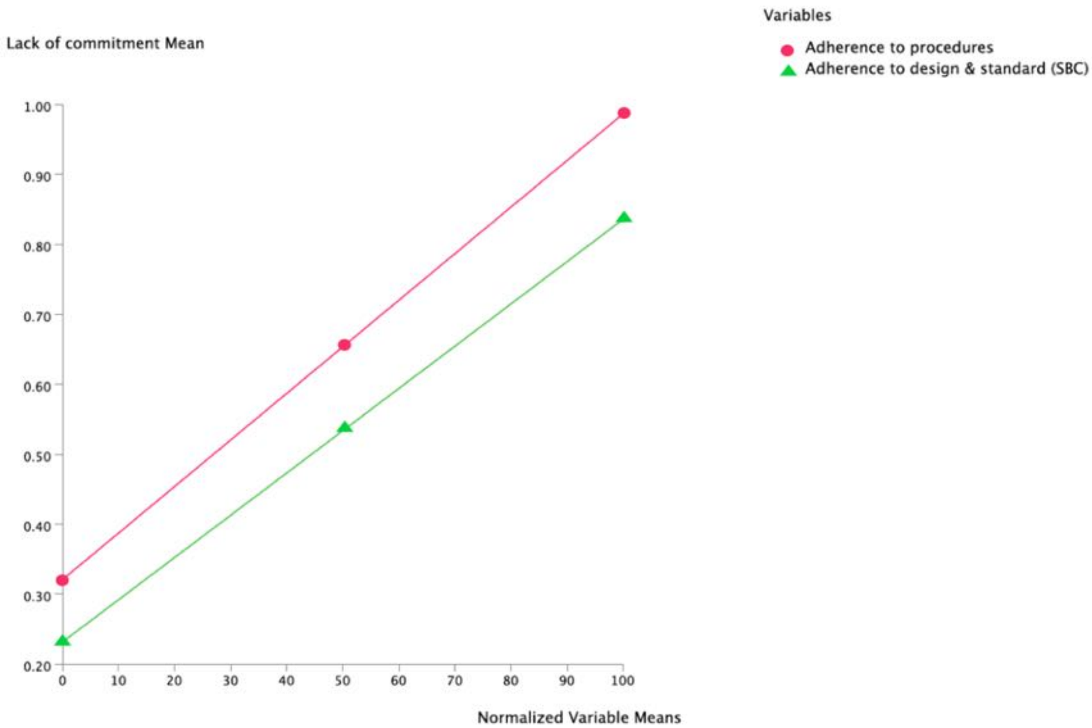
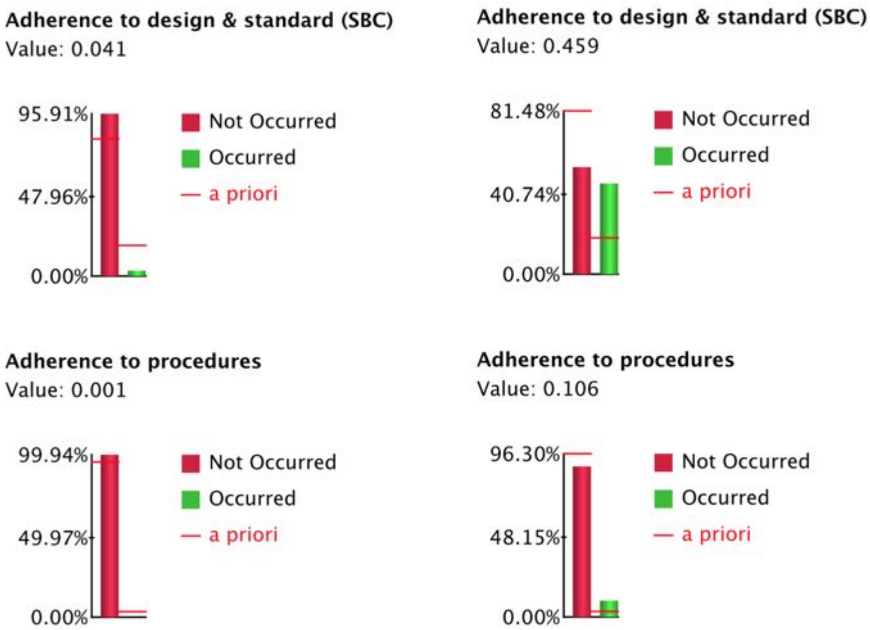


Figure 8.24 Direct effects of the potential causes of lack of commitment

The maximal variation was determined for the significant second-level causes, namely, 'adherence to design & standard' and 'adherence to procedures'. The occurrence and non-occurrence of 'lack of commitment' in relation to occurrence and non-occurrence 'adherence to design & standard' and 'adherence to procedures' were analyzed. When there is non-occurrence of 'lack of commitment', the model predicts the probability of 'adherence to design & standard' and 'adherence to procedures' non-occurrence increases (as shown in Table 8.15). The maximal variation is 14.43% and 3.645% (negative variation) respectively (as shown in Figure 8.25 (a)).

In contrast, when there is occurrence of 'lack of commitment', the model predicts the probability of 'adherence to design & standard' and 'adherence to procedures' occurrence to increase. The maximal variation is 27.41% and 6.921% (positive variation) respectively (as shown in Figure 8.25 (b)). 'Adherence to design & standard' and 'adherence to procedures' are the second-level causes most likely to underpin 'lack of commitment'.



(a) Lack of commitment*:* *Not occurred*

(b) Lack of commitment*:* *Occurred*

Figure 8.25 *Maximal variation* of adherence to design & standard & procedures

8.3.2.5 Second-level Causes of the First-level Cause 'Lack of Skills'

The independence tests *Chi–square* χ^2 show a significant association between 'work accurately' and 'handle with material/equipment' with the 'lack of skills'; χ^2 (1) = 11.43, (p< 0.05), and χ^2 (1) = 10.43, (p< 0.05) respectively (as shown in Table 8.15). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association (p> 0.05). The results support that only 'work accurately' and 'handle with material/equipment' is significantly associated with 'lack of skills'.

'Work accurately' and 'handle with material/equipment' were found have highest direct effect on first-level causes 'lack of skills', at 0.292 and 0.461 (as shown in

Figure 8.26). Also, MI amount of information brought by second-level causes ‘work accurately’ and ‘handle with material/equipment’ to first-level causes ‘lack of skills’ were *I*(‘work accurately’; ‘lack of skills’) = 0.0611 and *I*(‘handle with material/equipment’; ‘lack of skills’) = 0.0558 (as shown in Table 8.15 and Figure 8.17). ‘Work accurately’ and ‘handle with material/equipment’ have the highest MI with ‘lack of skills’ indicating a more dependent relationship between the second-level causes and the first-level causes.

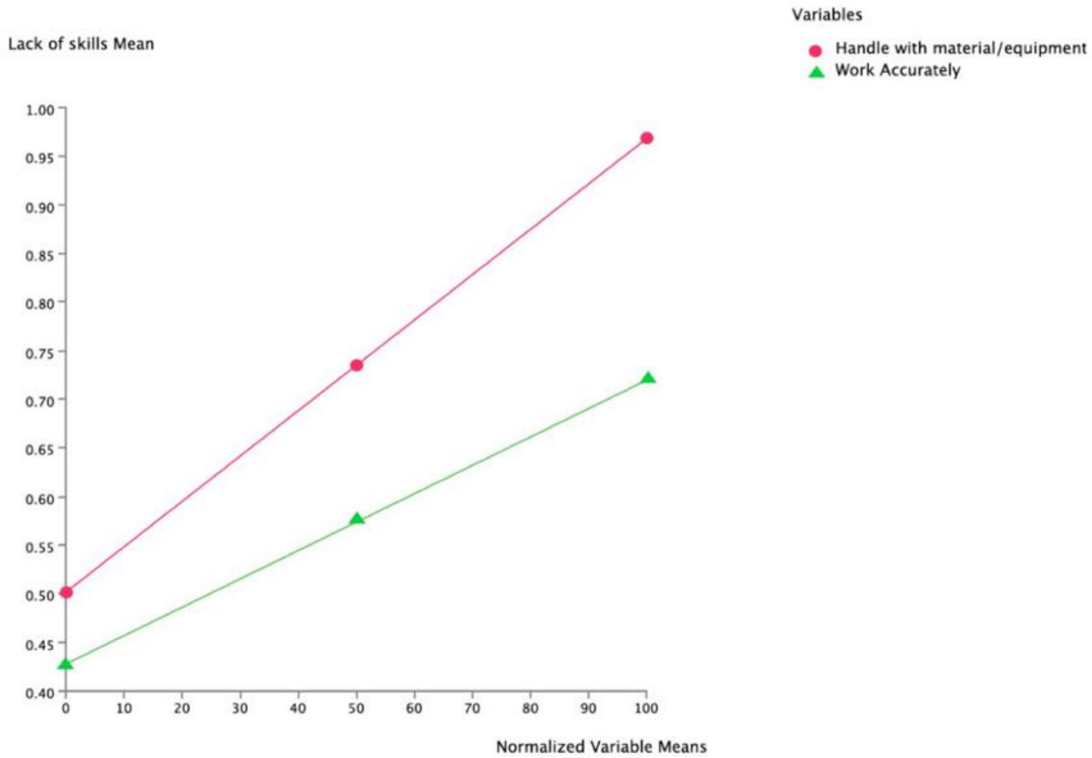
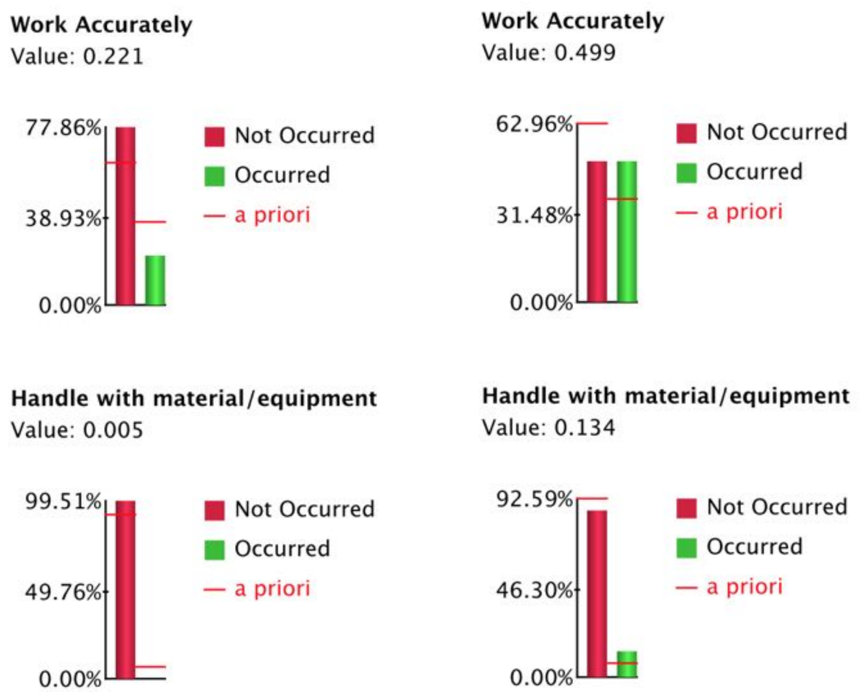


Figure 8.26 Direct effects of the potential causes of lack of skills

The maximal variation was determined for the significant second-level causes, namely, ‘work accurately’ and ‘handle with material/equipment’. The occurrence and non-occurrence of ‘lack of skills’ in relation to occurrence and non-occurrence ‘work accurately’ and ‘handle with material/equipment’ were analyzed. When there is non-occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ and ‘handle with material/equipment’ non-occurrence increases (as shown in Table 8.15). The maximal variation is 14.90% and 6.920%((negative variation) respectively (as shown in Figure 8.27 (a)).

In contrast, when there is occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ and ‘handle with material/equipment’ occurrence to increase. The maximal variation is 12.90% and 5.992% (positive variation) respectively (as shown in Figure 8.27 (b)). ‘Work accurately’ and ‘handle with material/equipment’ are the second-level causes most likely to underpin ‘lack of skills’.



(a) Lack of skills*:* *Not occurred*

(b) Lack of skills*:* *Occurred*

Figure 8.27 *Maximal variation* of work accurately & handle with material/equipment

8.3.3 STR.13

8.3.3.1 Direct Factors with STR.13

The independence tests *Chi–square* χ^2 show a significant association between 'worker-related underperformance' with the STR.13; χ^2 (2) = 9.386, (p< 0.05) (as shown in Table 8.16). The *Chi–square* χ^2 test results for the remaining direct factors fail to show a significant association (p> 0.05). The results support that only 'worker-related underperformance' is significantly associated with STR.13 performance.

'Worker-related underperformance' was found has highest direct effect on the target node STR.13, at 0.366 (as shown in Figure 8.28). Also, MI amount of information brought by the direct factors to the target variable STR.13 was I('worker-related underperformance'; 'STR.13') = 0.0244 (as shown in Table 8.16 and Figure 8.29). 'Worker-related underperformance' has the highest MI with STR.13 indicating a more dependent relationship between these direct factors and the target variable.

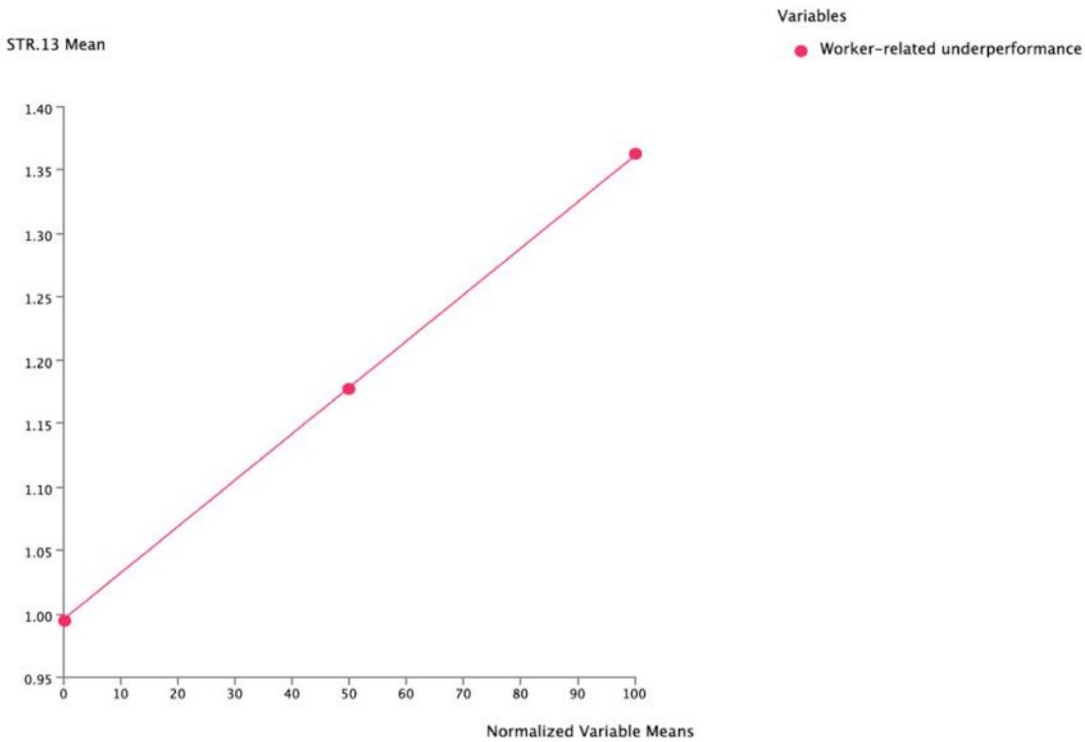


Figure 8.28 Direct effects of the direct factors of STR.13

Table 8.16 Statistical analyses of the significant causes of STR.13

Node	Priori Modal Value		Mean μ Value	χ^2	*df*	p-value	Direct Effect	MI	Modal Value		Maximal Variation	
	Not Occurred	*Occurred*							*State*	%	Positive	Negative
STR.13	**Scenario 1: Defective work**											
Worker-related underperformance	83.24%	16.76%	0.1676	9.386	2	0.0092	0.366	0.0244	*Occurred*	74.16%	9.076%	9.076%
STR.13	**Scenario 2: Acceptable work**											
Worker-related underperformance	83.24%	16.76%	0.1676	9.386	2	0.0092	0.366	0.0244	*Not Occurred*	88.49%	5.255%	5.255%
STR.13	**Scenario 3: Perfect work**											
Worker-related underperformance	83.24%	16.76%	0.1676	9.386	2	0.0092	0.366	0.0244	*Not Occurred*	88.73%	5.487%	5.487%
Worker-related underperformance	**Scenario 1: Not Occurred**											
Lack of skills	32.92%	67.08%	0.6708	87.49	1	0.0000	0.118	0.0188	*Not Occurred*	63.84%	3.241%	3.241%
Lack of commitment	63.85%	36.15%	0.3615	53.58	1	0.0000	0.093	0.0107	*Not Occurred*	66.52%	2.669%	2.669%
Lack of knowledge	51.49%	48.51%	0.4851	60.06	1	0.0000	0.030	0.0013	*Not Occurred*	52.43%	0.941%	0.941%
Worker-related underperformance	**Scenario 2: Occurred**											
Lack of skills	32.92%	67.08%	0.6708	87.49	1	0.0000	0.118	0.0188	*Occurred*	83.18%	16.09%	16.09%
Lack of commitment	63.85%	36.15%	0.3615	53.58	1	0.0000	0.093	0.0107	*Occurred*	50.59%	13.26%	13.26%
Lack of knowledge	51.49%	48.51%	0.4851	60.06	1	0.0000	0.030	0.0013	*Occurred*	53.18%	4.671%	4.671%
Lack of skills	**Scenario 1: Not Occurred**											
Work Accurately	25.93%	74.07%	0.7407	68.01	1	0.0000	0.745	0.3634	*Not Occurred*	69.97%	44.04%	44.04%
Lack of skills	**Scenario 2: Occurred**											
Work Accurately	25.93%	74.07%	0.7407	68.01	1	0.0000	0.745	0.3634	*Occurred*	95.68%	21.61%	21.61%
Lack of commitment	**Scenario 1: Not Occurred**											
Adherence to design & standard (SBC)	40.74%	59.26%	0.5926	182.49	1	0.0000	0.098	0.0076	*Not Occurred*	55.49%	3.766%	3.766%
Lack of commitment	**Scenario 2: Occurred**											
Adherence to design & standard (SBC)	40.74%	59.26%	0.5926	182.49	1	0.0000	0.098	0.0076	*Occurred*	65.91%	6.651%	6.651%
Lack of knowledge	**Scenario 1: Not Occurred**											
Dimensions required	37.04	62.96	0.6296	5.656	1	0.0174	0.210	0.0302	*Not Occurred*	53.42%	9.539%	9.539%
Lack of knowledge	**Scenario 2: Occurred**											
Dimensions required	37.04	62.96	0.6296	5.656	1	0.0174	0.210	0.0302	*Occurred*	73.08%	10.126%	10.126%

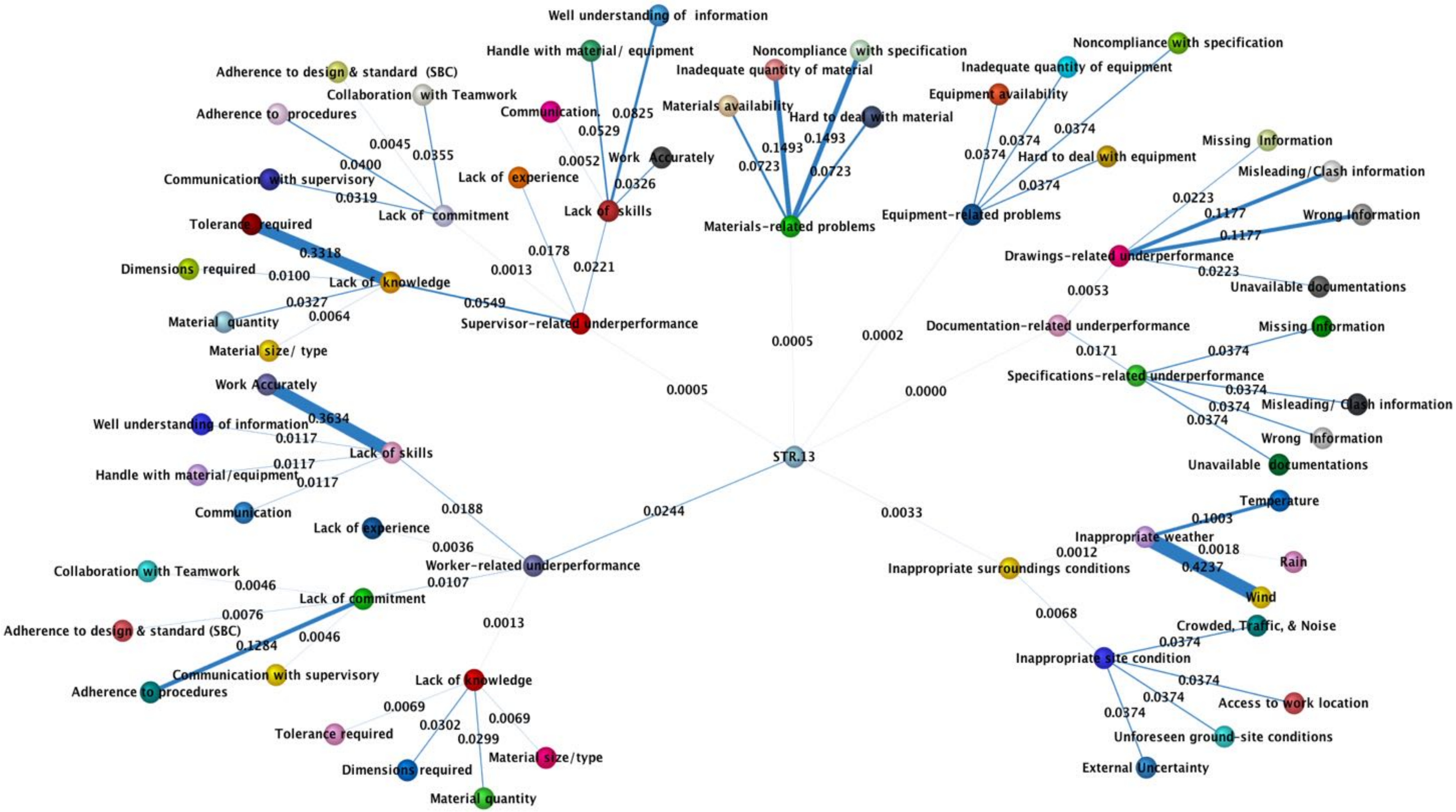


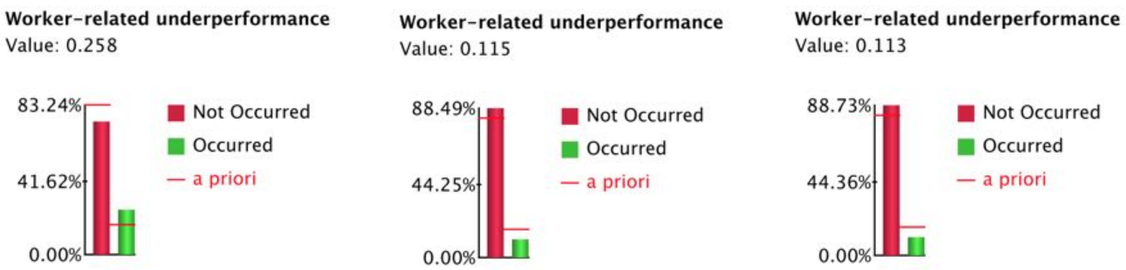
Figure 29 MI of STR.13 network

The maximal variation of the significant direct factors, namely, 'worker-related underperformance', as shown in the previous tests: the *Chi–square* χ^2 test, direct effect and the mutual information MI was calculated.

Performance of STR.13 could be 'perfect-work', 'acceptable-work' or 'defective-work'. When 'defective-work' was observed (i.e., the state of the quality output for executing STR.13 is defective-work), the model predicted that the probability of 'worker-related underperformance' occurrence increased. The maximal variation was 9.076% (positive variation) (as shown in Table 8.16 and Figure 8.30 (a)). 'Worker-related underperformance' is direct factors most prone to cause 'defective-work' in relation to STR.13.

When 'acceptable-work' was observed (i.e., the state of the quality output for executing STR.13 is acceptable-work), the model predicted that the probability of 'worker-related underperformance' occurrence decreased. The maximal variation was 5.255% (negative variation) respectively (as shown in Table 8.16 and Figure 8.30 (b)). 'Worker-related underperformance' is direct factors less prone to cause 'acceptable-work'.

Similarly, when 'perfect-work' was observed (i.e., the state of the quality output for executing STR.13 is perfect-work), the model predicted that the probability of 'worker-related underperformance' non-occurrence increased (negative variation). The maximal variation was 5.487% (as shown in Table 8.16 and Figure 8.30 (c)). 'Worker-related underperformance' is direct factor less prone to cause 'perfect-work'.



(a) Defective work (b) Acceptable work (c) Perfect work

Figure 8.30 *Maximal variation* of the direct factors of STR.13

8.3.3.2 First-level Causes of the Direct Factors 'Worker-related underperformance'

The independence tests *Chi–square* χ^2 show a significant association between 'lack of skills', 'lack of commitment' and 'lack of knowledge' with the 'worker-related underperformance'; χ^2 (1) = 87.49, (p< 0.05), χ^2 (1) = 53.58, (p< 0.05), and χ^2 (1) = 60.06, (p< 0.05) (as shown in Table 8.16). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association (p> 0.05). The results support that only 'lack of skills', 'lack of commitment' and 'lack of knowledge' are significantly associated with 'worker-related underperformance'.

'Lack of skills', 'lack of commitment' and 'lack of knowledge' were found have highest direct effect on direct factor 'worker-related underperformance', at 0.118, 0.093 and 0.030 respectively (as shown in Figure 8.31). Also, MI amount of information brought by first-level causes 'lack of skills', 'lack of commitment' and 'lack of knowledge' to direct factor 'worker-related underperformance' were I('lack of skills'; 'worker-related underperformance') = 0.0188, I('lack of commitment'; 'worker-related underperformance') = 0.0107 and I('lack of knowledge'; 'worker-related underperformance') = 0.0013 (as shown in Table 8.16 and Figure 8.29). 'lack of skills', 'lack of commitment' and 'lack of knowledge' have the highest MI with 'worker-related underperformance' indicating a more dependent relationship between the first-level causes and the direct factor.

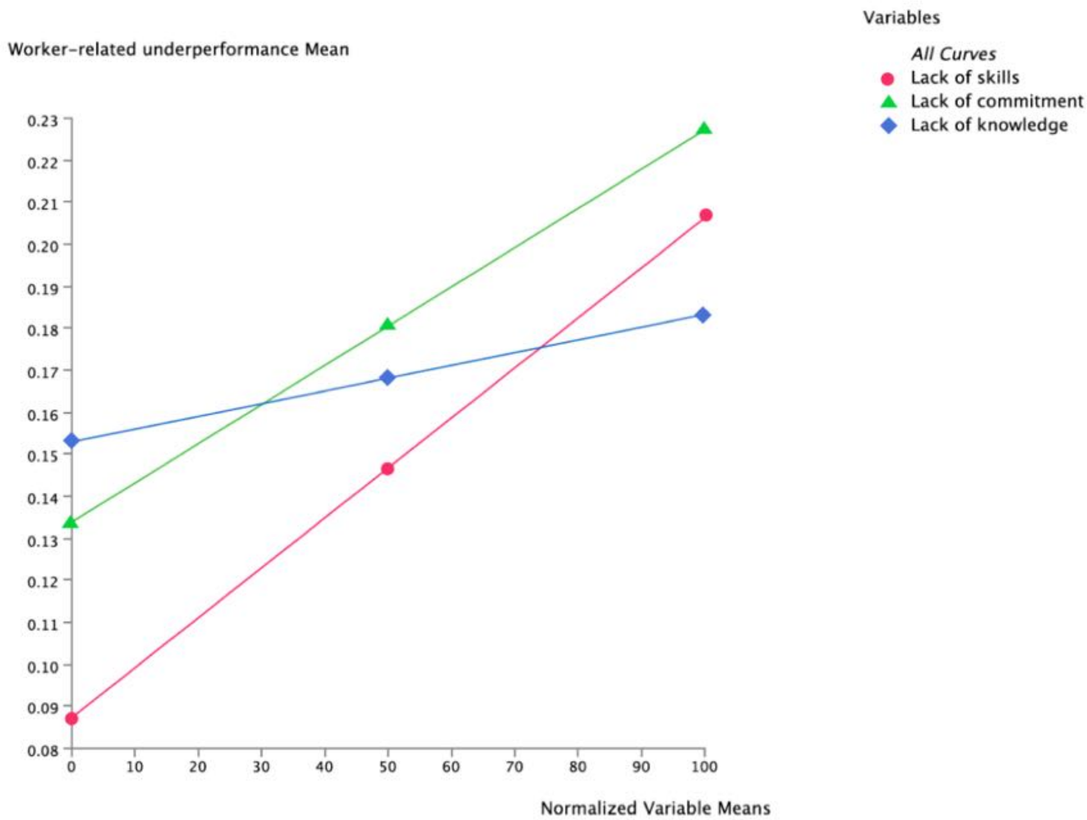


Figure 8.31 Direct effects of the potential causes of worker-related underperformance

The maximal variation was determined for the significant first-level cause, namely, 'lack of skills', 'lack of commitment' and 'lack of knowledge'. The occurrence and non-occurrence of 'worker-related underperformance' in relation to occurrence and non-occurrence 'lack of skills', 'lack of commitment' and 'lack of knowledge' were analyzed. When there is non-occurrence of 'worker-related underperformance', the model predicts the probability of 'lack of skills', 'lack of commitment' and 'lack of knowledge' non-occurrence increases (as shown in Table 8.16). The maximal variation is 3.241%, 2.669% and 0.941% (negative variation) respectively (as shown in Figure 8.32 (a)).

In contrast, when there is occurrence of 'worker-related underperformance', the model predicts the probability of 'lack of skills', 'lack of commitment' and 'lack of knowledge' occurrence to increase. The maximal variation is 16.09%, 13.26% and 4.671% (positive variation) respectively (as shown in Figure 8.32 (b)). 'Lack of skills', 'lack of commitment' and 'lack of knowledge' are the first-level cause most likely to underpin 'worker-related underperformance'.

(a) Worker-related underperformance: *Not occurred* (b) Worker-related underperformance: *Occurred*

Figure 8.32 *Maximal variation* of lack of skills, commitment & knowledge

8.3.3.3 Second-level Causes of the First-level Cause 'Lack of Skills'

The independence tests *Chi–square* χ^2 show a significant association between 'work accurately' with the 'lack of skills'; χ^2 (1) = 68.01, (p< 0.05) (as shown in Table 8.16). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association (p> 0.05). The results support that only 'work accurately' is significantly associated with 'lack of skills'.

‘Work accurately’ was found have highest direct effect on first-level causes ‘lack of skills’, at 0.745 (as shown in Figure 8.33). Also, MI amount of information brought by second-level causes ‘work accurately’ to first-level causes ‘lack of skills’ was *I*(‘work accurately’; ‘lack of skills’) = 0.3634 (as shown in Table 8.16 and Figure 8.29). ‘Work accurately’ has the highest MI with ‘lack of skills’ indicating a more dependent relationship between the second-level causes and the first-level causes.

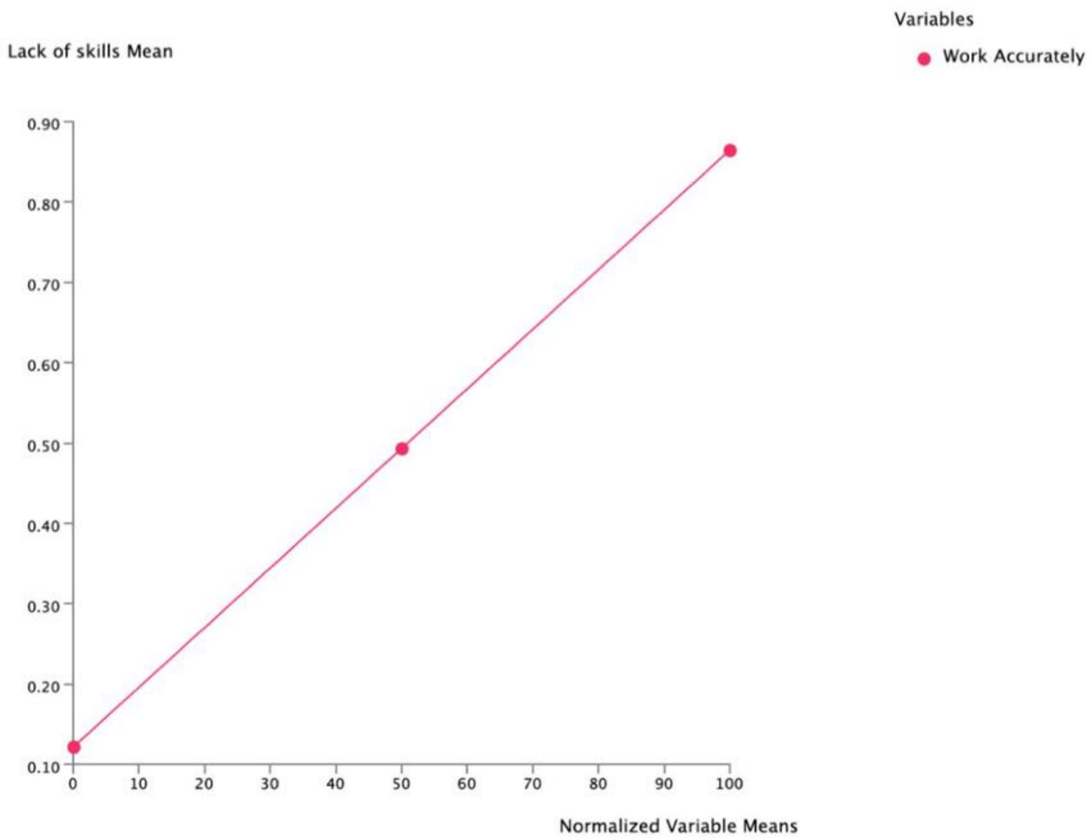
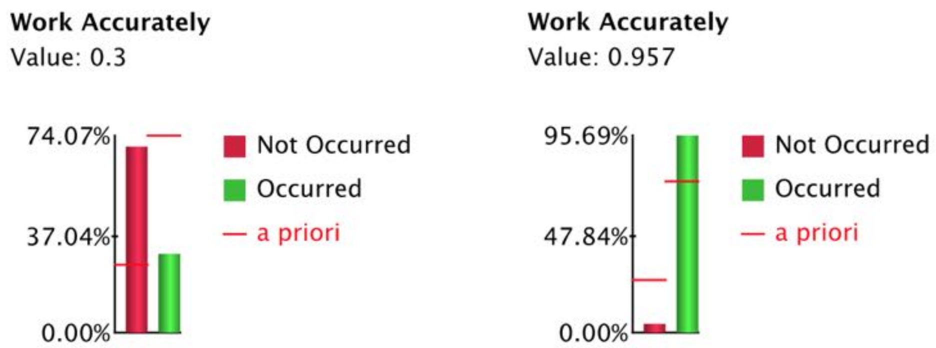


Figure 8.33 Direct effects of the potential causes of lack of skills

The maximal variation was determined for the significant second-level causes, namely, ‘work accurately’. The occurrence and non-occurrence of ‘lack of skills’ in relation to occurrence and non-occurrence ‘work accurately’ was analyzed. When there is non-occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ non-occurrence increases (as shown in Table 8.16). The maximal variation is 44.04% (negative variation) (as shown in Figure 8.34 (a)).

In contrast, when there is occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ occurrence to increase. The maximal variation is 21.61% (positive variation) (as shown in Figure 8.34 (b)). ‘Work accurately’ is the second-level causes most likely to underpin ‘lack of skills’.



(a) Lack of skills: *Not occurred*

(b) Lack of skills: *Occurred*

Figure 8.34 *Maximal variation* of work accurately

8.3.3.4 Second-level Causes of the First-level Cause ‘Lack of Commitment’

The independence tests *Chi–square* χ^2 show a significant association between ‘adherence to design & standard’ with the ‘lack of commitment’; χ^2 (1) = 182.49, ($p<$ 0.05) (as shown in Table 8.16). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association ($p>$ 0.05). The results support that only ‘adherence to design & standard’ is significantly associated with ‘lack of commitment’.

‘Adherence to design & standard’ was found have highest direct effect on first-level causes ‘lack of commitment’, at 0.098 (as shown in Figure 8.35). Also, MI amount of information brought by second-level causes ‘adherence to design & standard’ to first-level causes ‘lack of commitment’ was *I*(‘adherence to design & standard’; ‘lack of commitment’) = 0.0076 (as shown in Table 8.16 and Figure 8.29). ‘Adherence to design & standard’ has the highest MI with ‘lack of commitment’ indicating a more dependent relationship between the second-level causes and the first-level causes.

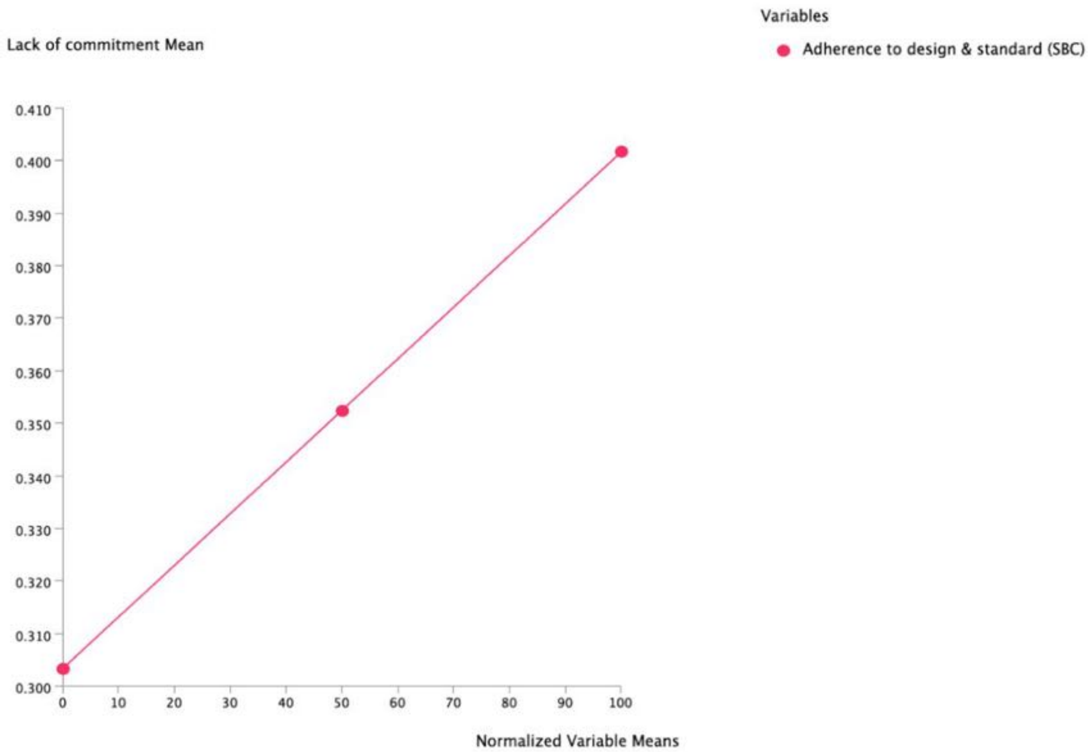
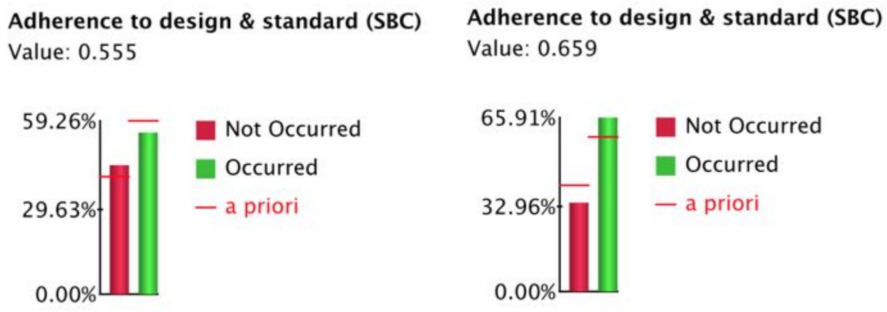


Figure 8.35 Direct effects of the potential causes of lack of commitment

The maximal variation was determined for the significant second-level causes, namely, 'adherence to design & standard'. The occurrence and non-occurrence of 'lack of commitment' in relation to occurrence and non-occurrence 'adherence to design & standard' was analyzed. When there is non-occurrence of 'lack of commitment', the model predicts the probability of 'adherence to design & standard' non-occurrence increases (as shown in Table 8.16). The maximal variation is 3.766% (negative variation) (as shown in Figure 8.36 (a)).

In contrast, when there is occurrence of 'lack of commitment', the model predicts the probability of 'adherence to design & standard' occurrence to increase. The maximal variation is 6.651% (positive variation) (as shown in Figure 8.36 (b)). 'Adherence to design & standard' is the second-level causes most likely to underpin 'lack of commitment'.



(a) Lack of commitment: *Not occurred* (b) Lack of commitment: *Occurred*

Figure 8.36 *Maximal variation* of adherence to design & standard (SBC)

8.3.3.5 Second-level Causes of the First-level Cause 'Lack of Knowledge'

The independence tests *Chi–square* χ^2 show a significant association between 'dimension required' with the 'lack of knowledge'; χ^2 (1) = 5.656, ($p <$ 0.05) (as shown in Table 8.16). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association ($p >$ 0.05). The results support that only 'dimension required' is significantly associated with 'lack of knowledge'.

'Dimension required' was found have highest direct effect on first-level causes 'lack of knowledge', at 0.210 (as shown in Figure 8.37). Also, MI amount of information brought by second-level causes 'dimension required' to first-level causes 'lack of knowledge' was *I*('dimension required'; 'lack of knowledge') = 0.0302 (as shown in Table 8.16 and Figure 8.29). 'Dimension required' has the highest MI with 'lack of knowledge' indicating a more dependent relationship between the second-level causes and the first-level causes.

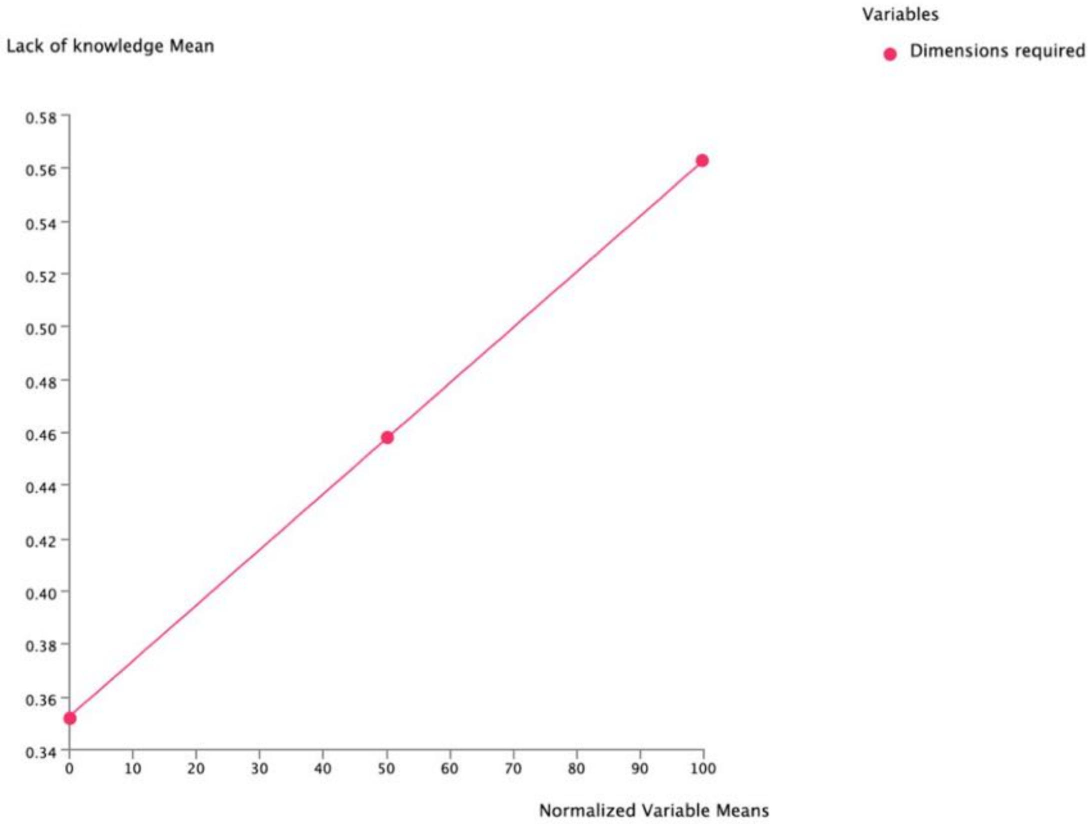
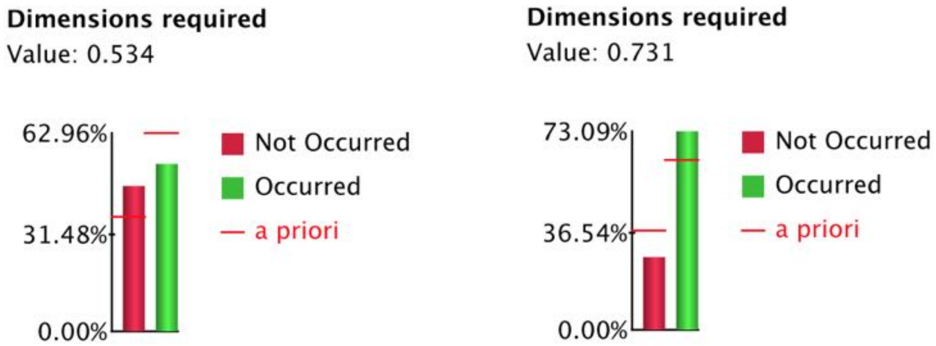


Figure 8.37 Direct effects of the potential causes of lack of knowledge

The maximal variation was determined for the significant second-level causes, namely, 'dimension required'. The occurrence and non-occurrence of 'lack of knowledge' in relation to occurrence and non-occurrence 'dimension required' was analyzed. When there is non-occurrence of 'lack of knowledge', the model predicts the probability of 'dimension required' non-occurrence increases (as shown in Table 8.16). The maximal variation is 9.539% (negative variation) (as shown in Figure 8.38 (a)).

In contrast, when there is occurrence of 'lack of knowledge', the model predicts the probability of 'dimension required' occurrence to increase. The maximal variation is 10.126% (positive variation) (as shown in Figure 8.38 (b)). 'Dimension required' is the second-level causes most likely to underpin 'lack of knowledge'.



(a) Lack of knowledge: *Not occurred*

(b) Lack of knowledge: *Occurred*

Figure 8.38 *Maximal variation* of dimension required

8.3.4 STR.15

8.3.4.1 Direct Factors with STR.15

The independence tests *Chi–square* χ^2 show a significant association between 'equipment-related problems' and 'worker-related underperformance' with the STR.15; χ^2 (2) = 10.39, (p< 0.05), and; χ^2 (2) = 3.128, (p< 0.05) respectively (as shown in Table 8.17). The *Chi–square* χ^2 test results for the remaining direct factors fail to show a significant association (p> 0.05). The results support that only 'equipment-related problems' and 'worker-related underperformance' is significantly associated with STR.15 performance.

'Equipment-related problems' and 'worker-related underperformance' were found have highest direct effect on the target node STR.15, at 0.170 and 0.304 respectively (as shown in Figure 8.39). Also, MI amount of information brought by the direct factors to the target variable STR.15 was *I*('equipment-related problems'; 'STR.15') = 0.0555, *I*('worker-related underperformance'; 'STR.5') = 0.0167 (as shown in Table 8.17 and Figure 8.40). 'Equipment-related problems' and 'worker-related underperformance' have the highest MI with STR.15 indicating a more dependent relationship between these direct factors and the target variable.

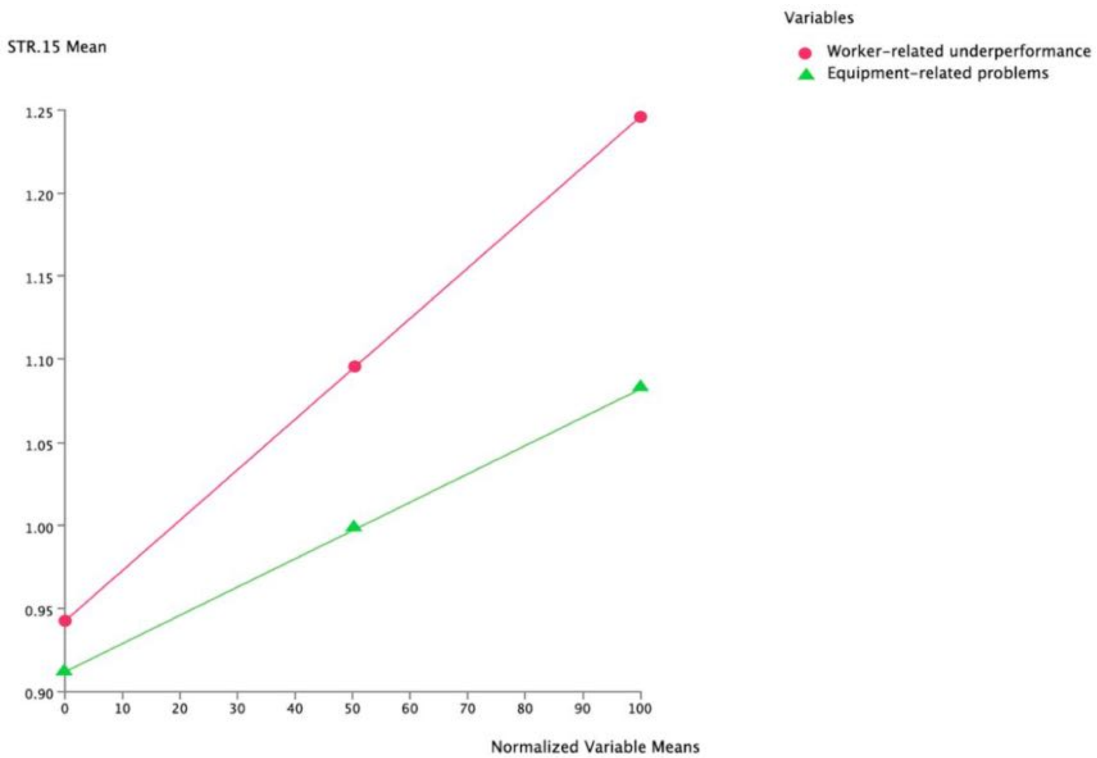


Figure 8.39 Direct effects of the potential causes of STR.15

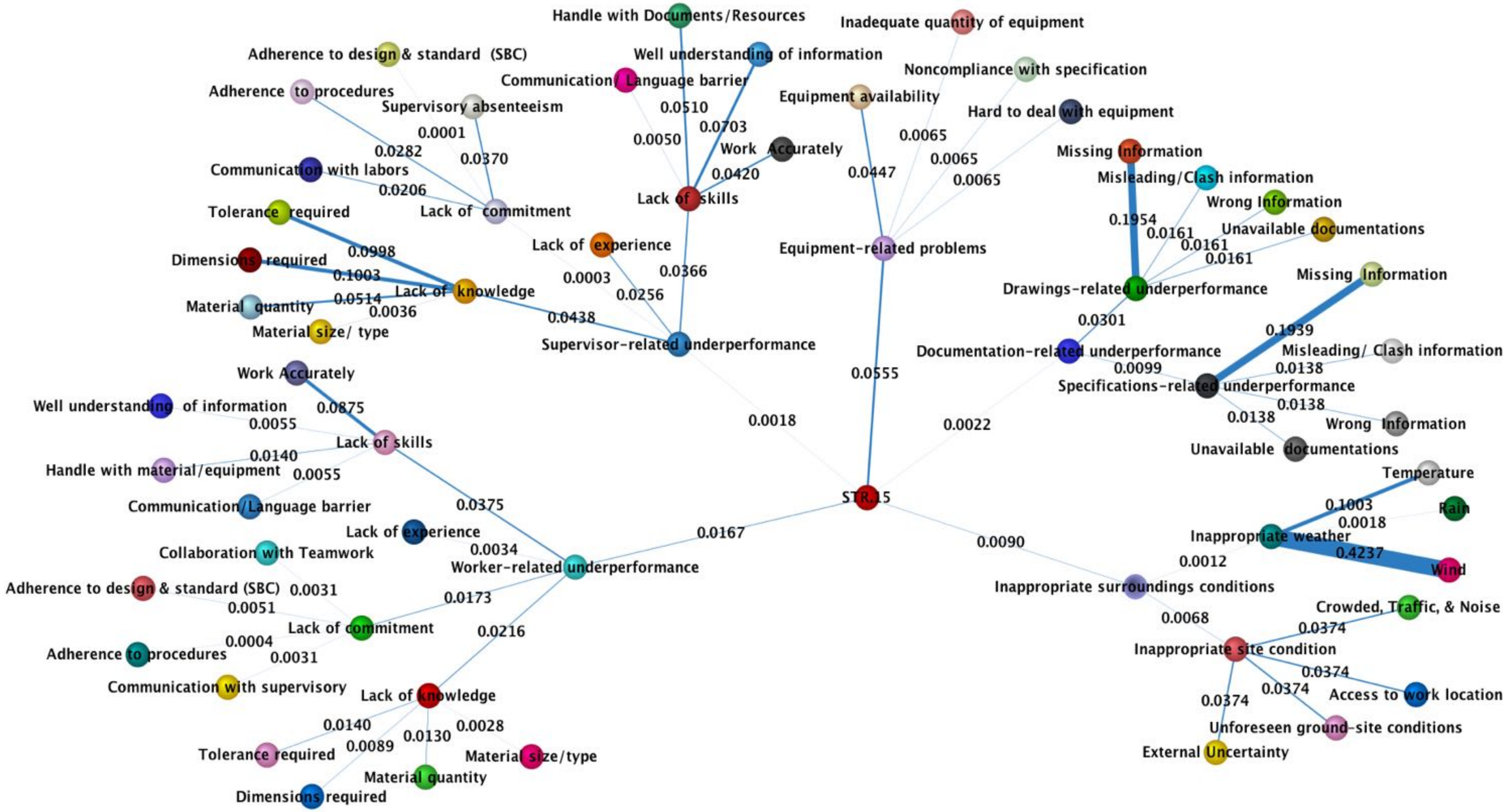


Figure 8.40 MI of STR.15 network

Table 8.17 Statistical analyses of the significant causes of STR.15

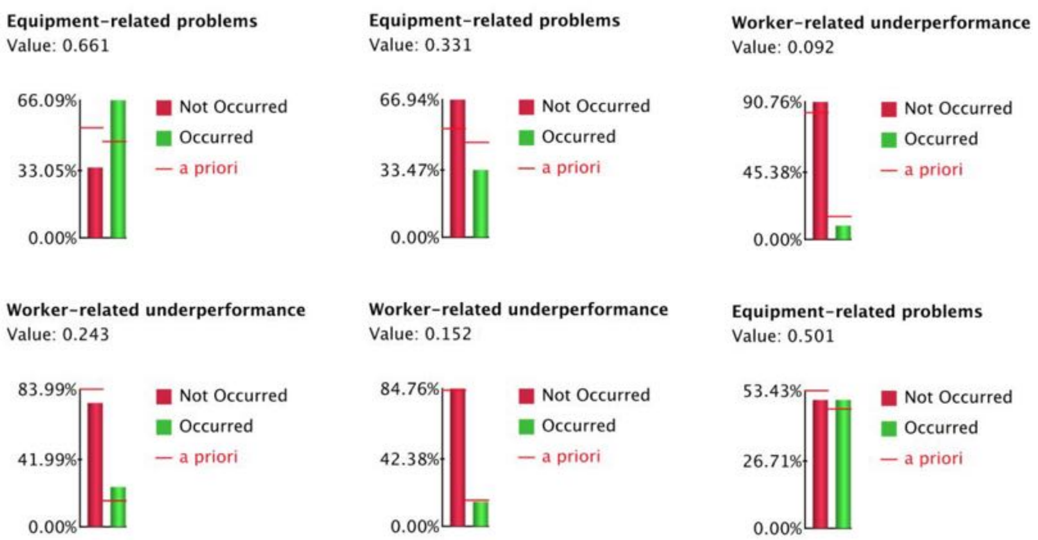
Node	*Priori Modal Value*		Mean μ Value	χ^2	*df*	p-value	Direct Effect	MI	Modal Value		Maximal Variation	
	Not Occurred	*Occurred*							*State*	%	Positive	Negative
STR.15	**Scenario 1: Defective work**											
Equipment-related problems	53.43%	46.57%	0.4657	10.39	2	0.0055	0.170	0.0555	*Occurred*	66.09%	19.52%	19.52%
Worker-related underperformance	83.99%	16.01%	0.1601	3.128	2	0.0209	0.304	0.0167	*Occurred*	75.68%	8.309%	8.3090%
STR.15	**Scenario 2: Acceptable work**											
Equipment-related problems	53.43%	46.57%	0.4657	10.39	2	0.0055	0.170	0.0555	*Not Occurred*	66.94%	13.51%	13.51%
Worker-related underperformance	83.99%	16.01%	0.1601	3.128	2	0.0209	0.304	0.0167	*Not Occurred*	84.76%	0.768%	0.768%
STR.15	**Scenario 3: Perfect work**											
Equipment-related problems	53.43%	46.57%	0.4657	10.39	2	0.0055	0.170	0.0555	*Occurred*	90.76%	6.768%	6.768%
Worker-related underperformance	83.99%	16.01%	0.1601	3.128	2	0.0209	0.304	0.0167	*Not Occurred*	50.09%	3.523%	3.523%
Equipment-related problems	**Scenario 1: Not Occurred**											
Equipment availability	59.26%	40.74%	0.4074	8.364	1	0.0038	0.233	0.0447	*Not Occurred*	70.63%	11.37%	11.37%
Equipment-related problems	**Scenario 2: Occurred**											
Equipment availability	59.26%	40.74%	0.4074	8.364	1	0.0038	0.233	0.0447	*Occurred*	53.78%	13.04%	13.04%
Worker-related underperformance	**Scenario 1: Not Occurred**											
Lack of skills	58.69%	41.31%	0.4131	7.026	1	0.0080	0.167	0.0375	*Not Occurred*	63.62%	4.931%	4.931%
Worker-related underperformance	**Scenario 2: Occurred**											
Lack of skills	58.69%	41.31%	0.4131	7.026	1	0.0080	0.167	0.0375	*Occurred*	67.17%	25.86%	25.86%
Lack of skills	**Scenario 1: Not Occurred**											
Work Accurately	25.93%	74.07%	0.7407	16.38	1	0.0001	0.353	0.0875	*Not Occurred*	61.91%	12.15%	12.15%
Lack of skills	**Scenario 2: Occurred**											
Work Accurately	25.93%	74.07%	0.7407	16.38	1	0.0001	0.353	0.0875	*Occurred*	91.34%	17.27%	17.27%

The maximal variation of the significant direct factors, namely, 'equipment-related problems' and 'worker-related underperformance', as shown in the previous tests: the *Chi–square* χ^2 test, direct effect and the mutual information MI was calculated.

Performance of STR.15 could be 'perfect-work', 'acceptable-work' or 'defective-work'. When 'defective-work' was observed (i.e., the state of the quality output for executing STR.15 is defective-work), the model predicted that the probability of 'equipment-related problems' and 'worker-related underperformance' occurrence increased. The maximal variation was 19.52% and 8.309% (positive variation) respectively (as shown in Table 8.17 and Figure 8.41 (a)). ‘Equipment-related problems’ and ‘worker-related underperformance’ are direct factors most prone to cause ‘defective-work’ in relation to STR.15.

When ‘acceptable-work’ was observed (i.e., the state of the quality output for executing STR.15 is acceptable-work), the model predicted that the probability of ‘equipment-related problems’ and ‘worker-related underperformance’ non-occurrence decreased. The maximal variation was 13.51% and 0.768% (negative variation) respectively (as shown in Table 8.17 and Figure 8.41 (b)). ‘Equipment-related problems’ and ‘worker-related underperformance’ is direct factors less prone to cause ‘acceptable-work’.

Similarly, when ‘perfect-work’ was observed (i.e., the state of the quality output for executing STR.15 is perfect-work), the model predicted that the probability of ‘equipment-related problems’ occurrence increased (positive variation) and ‘worker-related underperformance’ non-occurrence increased (negative variation). The maximal variation was 6.768% and 3.523% respectively (as shown in Table 8.17 and Figure 8.41 (c)). ‘Equipment-related problems’ and ‘worker-related underperformance’ are direct factor less prone to cause ‘perfect-work’.



(a) Defective work (b) Acceptable work (c) Perfect work

Figure 8.41 *Maximal variation* of the direct factors of STR.15

8.3.4.2 First-level Causes of the Direct Factors 'Equipment-related Problems'

The independence tests *Chi–square* χ^2 show a significant association between 'equipment availability' with the 'equipment-related problems'; χ^2 (1) = 8.364, ($p <$ 0.05) (as shown in Table 8.17). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p >$ 0.05). The results support that only 'equipment availability' is significantly associated with 'equipment-related problems'.

'Equipment availability' was found have highest direct effect on direct factor 'equipment-related problems', at 0.233 (as shown in Figure 8.42). Also, MI amount of information brought by first-level causes 'equipment availability' to direct factor 'equipment-related problems' *I*('equipment availability'; 'equipment-related problems') = 0.0447 (as shown in Table 8.17 and Figure 8.40). 'Equipment availability' has the highest MI with 'equipment-related problems' indicating a more dependent relationship between the first-level causes and the direct factor.

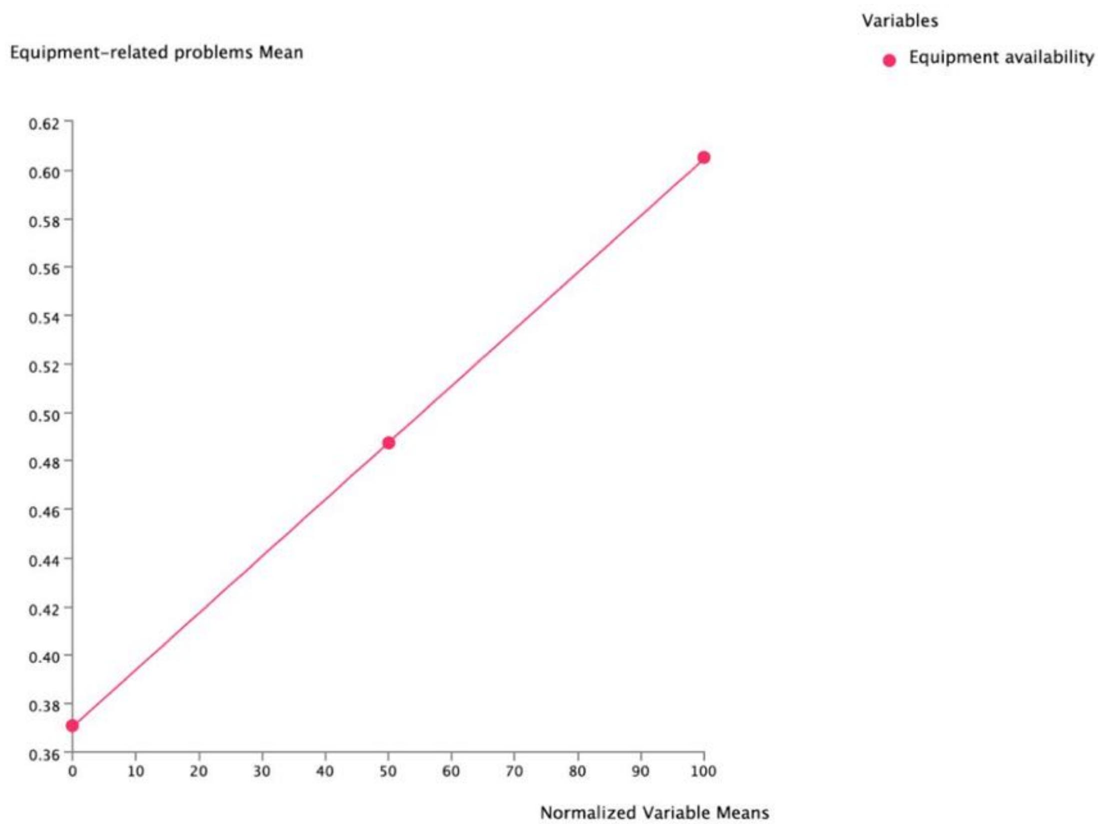
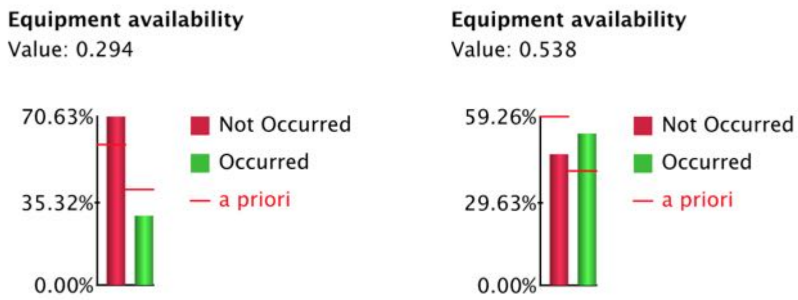


Figure 8.42 Direct effects of the potential causes of equipment-related problems

The maximal variation was determined for the significant first-level cause, namely, 'equipment availability'. The occurrence and non-occurrence of 'equipment-related problems' in relation to occurrence and non-occurrence 'equipment availability' was analyzed. When there is non-occurrence of 'equipment-related problems', the model predicts the probability of 'equipment availability' non-occurrence increases (as shown in Table 8.17). The maximal variation is 11.37%, (negative variation) (as shown in Figure 8.43 (a)).

In contrast, when there is occurrence of 'equipment-related problems', the model predicts the probability of 'equipment availability' occurrence to increase. The maximal variation is 13.04% (positive variation) (as shown in Figure 8.43 (b)). 'Equipment availability' is the first-level cause most likely to underpin 'equipment-related problems'.



(a) Equipment-related problems: *Not occurred*

(b) Equipment-related problems: *Occurred*

Figure 8.43 *Maximal variation* of the equipment availability

8.3.4.3 First-level Causes of the Direct Factors 'Worker-related Underperformance'

The independence tests *Chi–square* χ^2 show a significant association between 'lack of skills' with the 'worker-related underperformance'; χ^2 (1) = 7.026, ($p < 0.05$) (as shown in Table 8.17). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p > 0.05$). The results support that only 'lack of skills' is significantly associated with 'worker-related underperformance'.

'Lack of skills' was found have highest direct effect on direct factor 'worker-related underperformance', at 0.167 (as shown in Figure 8.44). Also, MI amount of information brought by first-level causes 'lack of skills' to direct factor 'worker-related underperformance' was *I*('lack of skills'; 'worker-related underperformance') = 0.0375 (as shown in Table 8.17 and Figure 8.40). 'Lack of skills' has the highest MI with 'worker-related underperformance' indicating a more dependent relationship between the first-level causes and the direct factor.

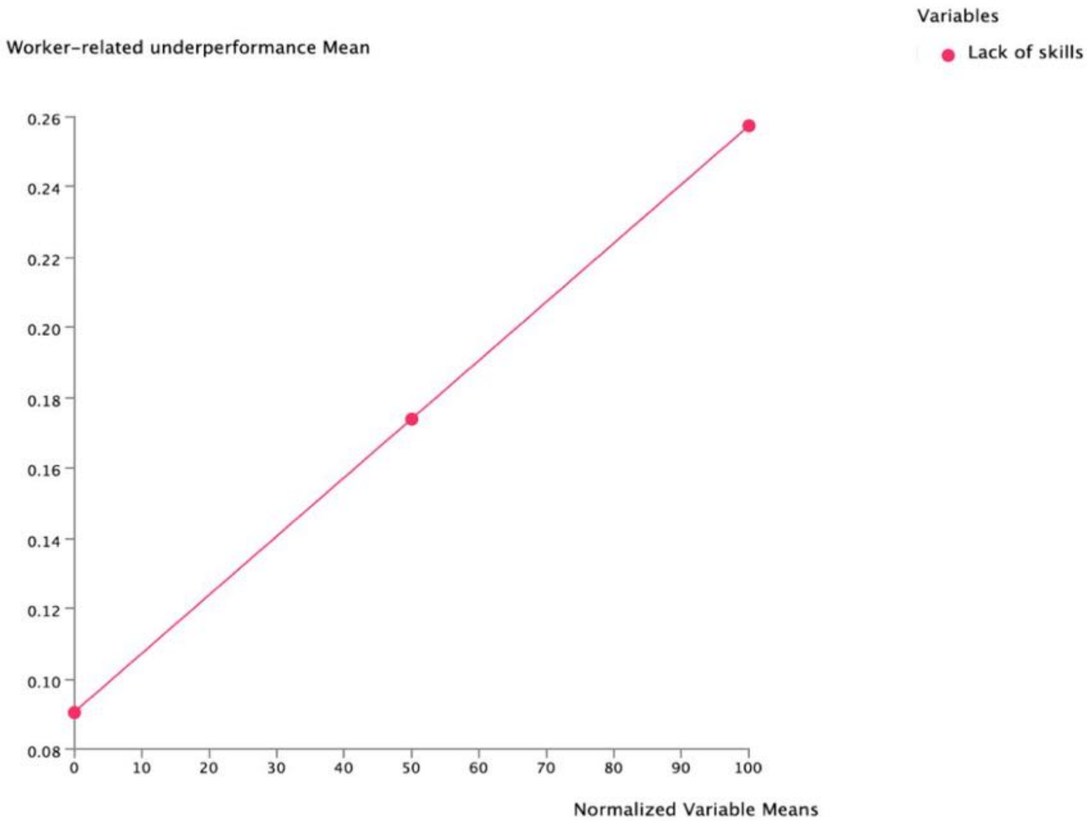
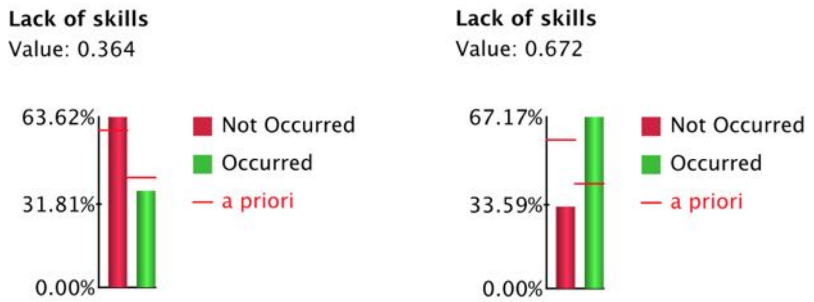


Figure 8.44 Direct effects of the potential causes of worker-related underperformance

The maximal variation was determined for the significant first-level cause, namely, 'lack of skills'. The occurrence and non-occurrence of 'worker-related underperformance' in relation to occurrence and non-occurrence 'lack of skills' was analyzed. When there is non-occurrence of 'worker-related underperformance', the model predicts the probability of 'lack of skills' non-occurrence increases (as shown in Table 8.17). The maximal variation is 4.931%, (negative variation) (as shown in Figure 8.45 (a)).

In contrast, when there is occurrence of ‘worker-related underperformance’, the model predicts the probability of ‘lack of skills’ occurrence to increase. The maximal variation is 25.86% (positive variation) (as shown in Figure 8.45 (b)). ‘Lack of skills’ is the first-level cause most likely to underpin ‘worker-related underperformance’.



(a) Worker-related underperformance: *Not occurred* (b) Worker-related underperformance: *Occurred*

Figure 8.45 *Maximal variation* of lack of skills

8.3.4.4 Second-level Causes of the First-level Cause ‘Lack of Skills’

The independence tests *Chi–square* χ^2 show a significant association between ‘work accurately’ with the ‘lack of skills’; χ^2 (1) = 16.38, (p< 0.05) (as shown in Table 8.17). The *Chi–square* χ^2 test results for the remaining second-level causes failed to show a significant association (p> 0.05). The results support that only ‘work accurately’ is significantly associated with ‘lack of skills’.

‘Work accurately’ was found have highest direct effect on first-level causes ‘lack of skills’, at 0.353 (as shown in Figure 8.46). Also, MI amount of information brought by second-level causes ‘work accurately’ to first-level causes ‘lack of skills’ was I(‘work accurately’; ‘lack of skills’) = 0.0875 (as shown in Table 8.17 and Figure 8.40). ‘Work accurately’ has the highest MI with ‘lack of skills’ indicating a more dependent relationship between the second-level causes and the first-level causes.

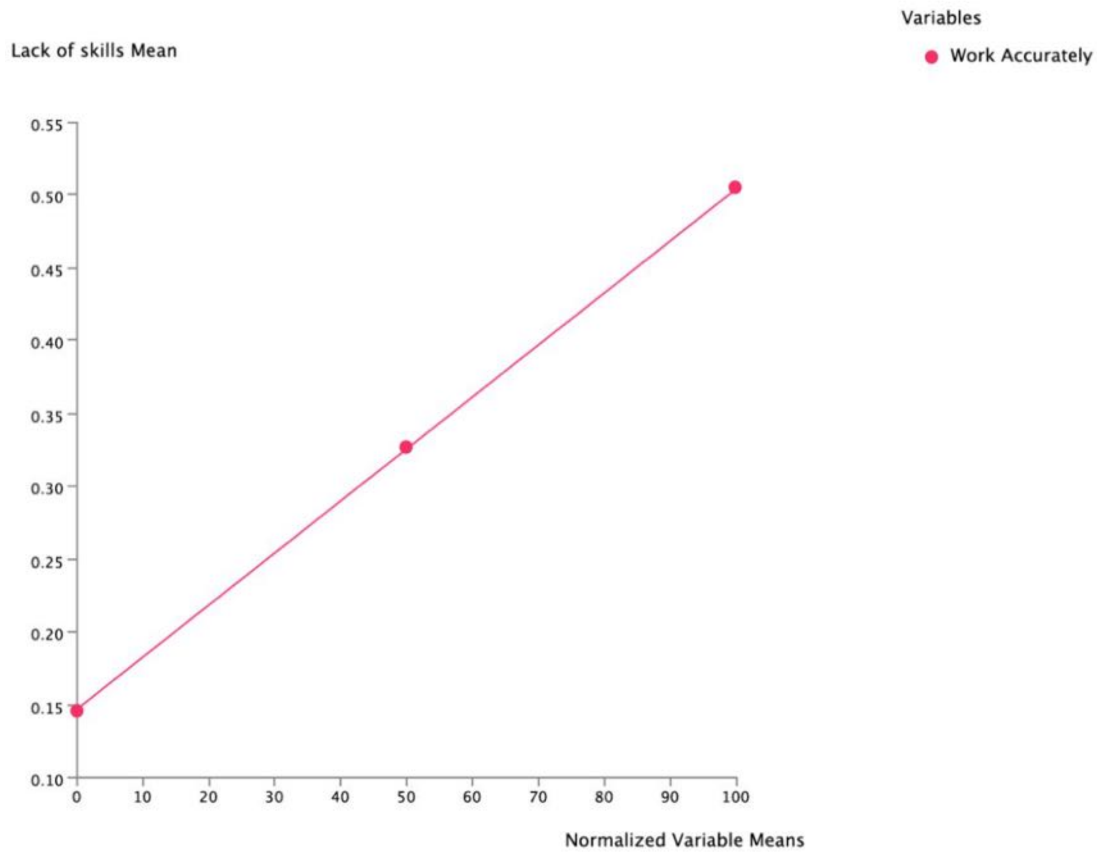
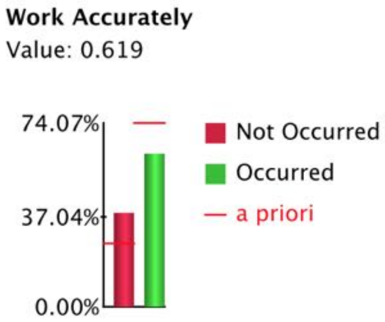


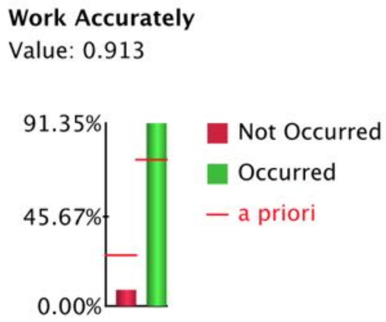
Figure 8.46 Direct effects of the potential causes of lack of skills

The maximal variation was determined for the significant second-level causes, namely, ‘work accurately’. The occurrence and non-occurrence of ‘lack of skills’ in relation to occurrence and non-occurrence ‘work accurately’ was analyzed. When there is non-occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ non-occurrence increases (as shown in Table 8.17). The maximal variation is 12.15% (negative variation) (as shown in Figure 8.47 (a)).

In contrast, when there is occurrence of ‘lack of skills’, the model predicts the probability of ‘work accurately’ occurrence to increase. The maximal variation is 17.27% (positive variation) (as shown in Figure 8.47 (b)). ‘Work accurately’ is the second-level causes most likely to underpin ‘lack of skills’.



(a) Lack of skills:
Not occurred



(b) Lack of skills:
Occurred

Figure 8.47 *Maximal variation* of work accurately

8.3.5 STR.16

8.3.5.1 Direct Factors with STR.16

The independence tests *Chi–square* χ^2 show a significant association between 'equipment-related problems' and 'inappropriate surroundings conditions' with the STR.16; χ^2 (2) = 6.392, (p< 0.05), and; χ^2 (4) = 47.47, (p< 0.05) respectively (as shown in Table 8.18). The *Chi–square* χ^2 test results for the remaining direct factors fail to show a significant association (p> 0.05). The results support that only 'equipment-related problems' and 'inappropriate surroundings conditions' are significantly associated with STR.16 performance.

'Equipment-related problems' and 'inappropriate surroundings conditions' were found have highest direct effect on the target node STR.16, at 0.235 and 0.126 respectively (as shown in Figure 8.48). Also, MI amount of information brought by the direct factors to the target variable STR.16 were I('equipment-related problems'; 'STR.16') = 0.0152, and I('inappropriate surroundings conditions'; 'STR.16') = 0.0185 (as shown in Table 8.18 and Figure 8.49). 'Equipment-related problems' and 'inappropriate surroundings conditions' have the highest MI with STR.16 indicating a more dependent relationship between these direct factors and the target variable.

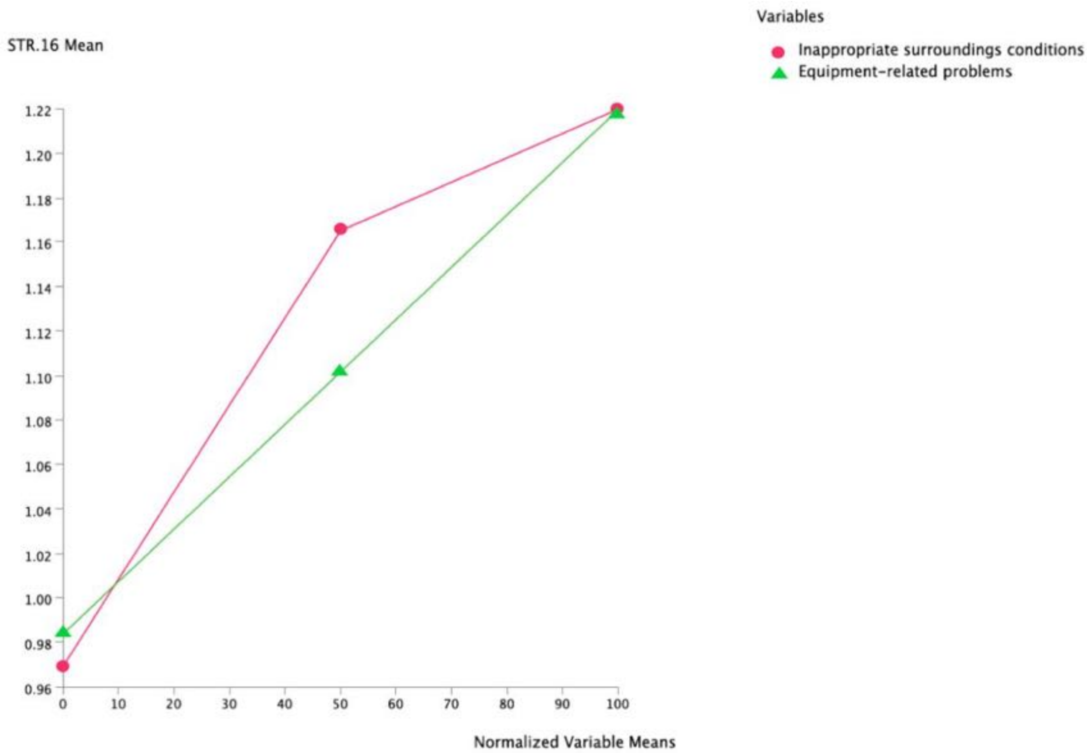


Figure 8.48 Direct effects of the potential causes of STR.16

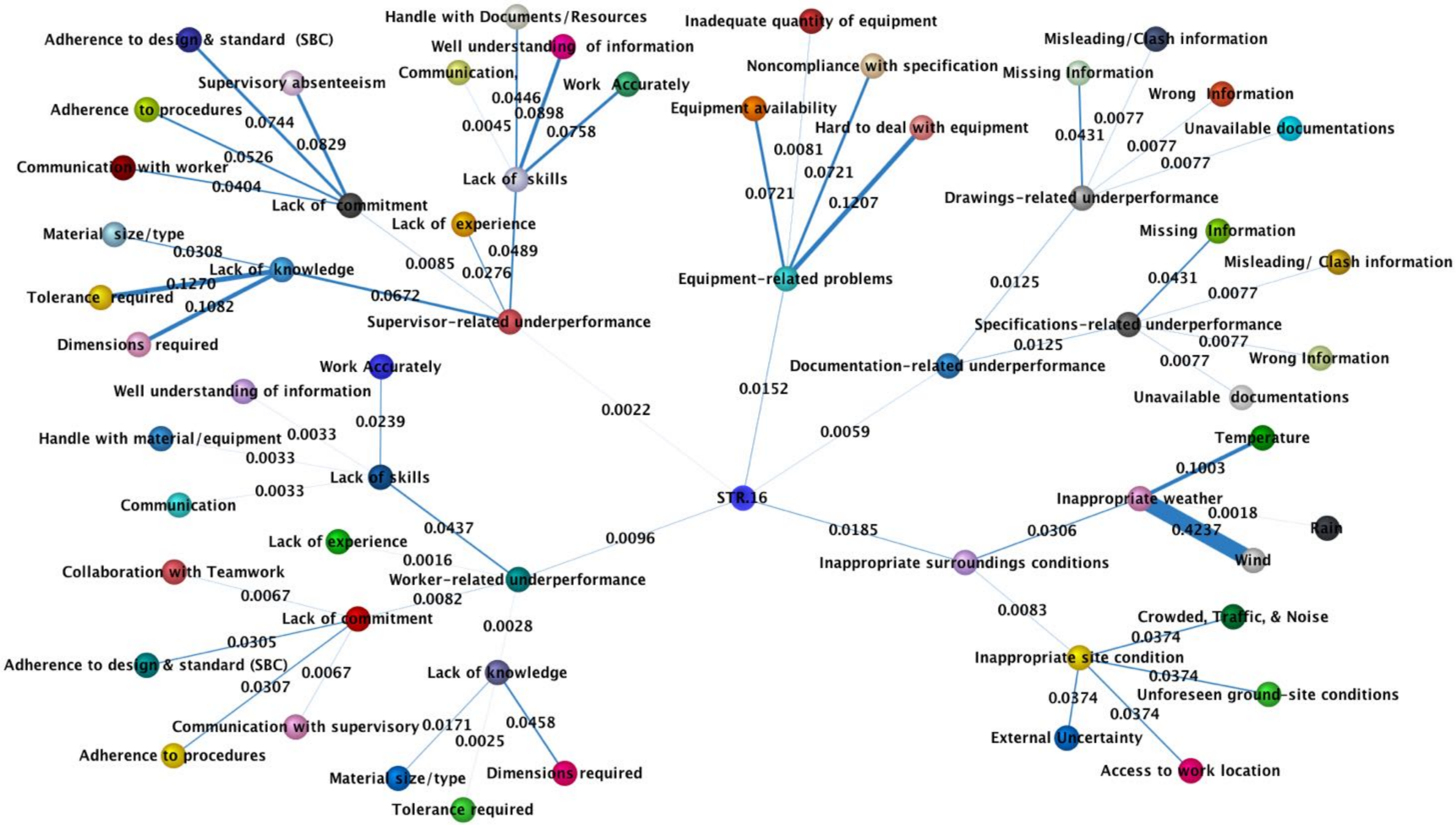


Figure 8.49 MI of STR.16 network

Table 8.18 Statistical analyses of the significant causes of STR.16

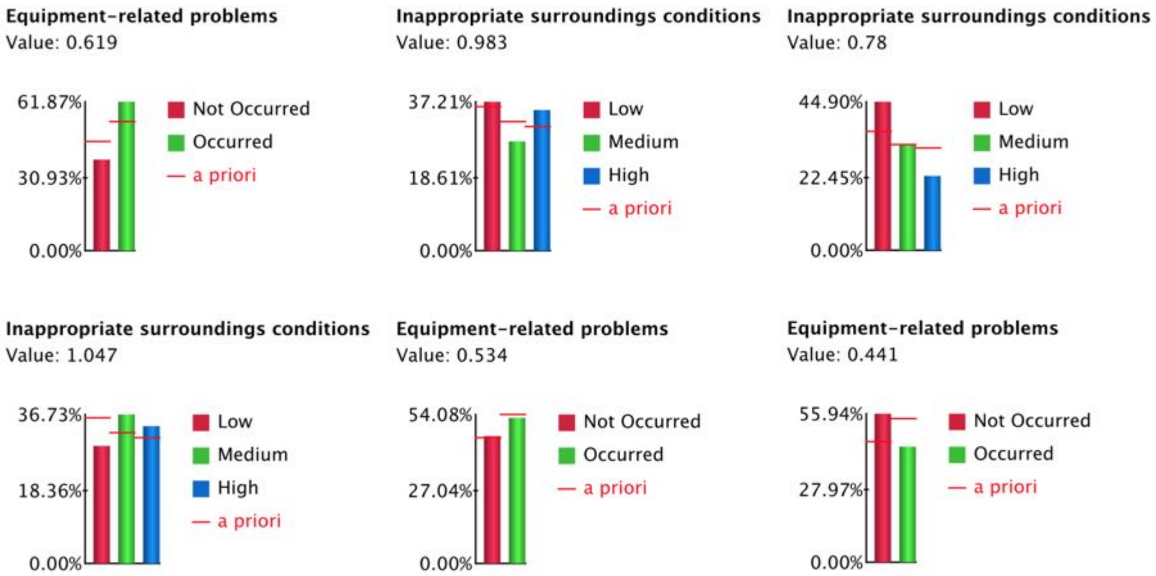
Node	*Priori Modal Value*	Mean μ	χ^2	*df*	p-value	Direct Effect	MI	Modal Value *State*	Modal Value %	Maximal Variation Positive	Maximal Variation Negative
STR.16	**Scenario 1: defective work**										
Equipment-related problems	*Not Occurred* 45.92% *Occurred* 54.08%	0.5408	6.392	2	0.0409	0.235	0.0152	*Occurred*	61.86%	7.783%	7.783%
Inappropriate surroundings cond.	L 36.26% M 32.37% H 31.37%	0.9511	47.47	4	0.0000	0.126	0.0185	*Medium*	36.72%	4.358%	6.979%
STR.16	**Scenario 2: acceptable work**										
Equipment-related problems	*Not Occurred* 45.92% *Occurred* 54.08%	0.5408	6.392	2	0.0409	0.235	0.0152	*Not Occurred*	53.36%	4.106%	5.059%
Inappropriate surroundings cond.	L 36.26% M 32.37% H 31.37%	0.9511	47.47	4	0.126	0. 126	0.0185	*Low*	37.21%	0.722%	0.722%
STR.16	**Scenario 3: perfect work**										
Equipment-related problems	*Not Occurred* 45.92% *Occurred* 54.08%	0.5408	6.392	2	0.0409	0.235	0.0152	*Not Occurred*	55.94%	8.634%	8.496%
Inappropriate surroundings cond.	L 36.26% M 32.37% H 31.37%	0.9511	47.47	4	0.126	0. 126	0.0185	*Low*	44.89%	10.02%	10.02%
Equipment-related problems	**Scenario 1: Not Occurred**										
Hard to deal with equipment	*Not Occurred* 18.52% *Occurred* 81.48%	0.8148	22.58	1	0.0000	0.497	0.1207	*Not Occurred*	64.87%	16.60%	16.60%
Equipment-related problems	**Scenario 2: Occurred**										
Hard to deal with equipment	*Not Occurred* 18.52% *Occurred* 81.48%	0.8148	22.58	1	0.0000	0.497	0.1207	*Occurred*	95.58%	14.10%	14.10%
Inappropriate surroundings cond.	**Scenario 1: High**										
Inappropriate weather	Low 13.76% Medium 58.54% High 27.70%	1.1394	90.97	4	0.0000	0.178	0.0306	*High*	60.21%	3.577%	5.259%
Inappropriate surroundings cond.	**Scenario 2: Medium**										
Inappropriate weather	Low 13.76% Medium 58.54% High 27.70%	1.1394	90.97	4	0.0000	0.178	0.0306	*Medium*	64.12%	5.591%	5.522%
Inappropriate surroundings cond.	**Scenario 3: Low**										
Inappropriate weather	Low 13.76% Medium 58.54% High 27.70%	1.1394	90.97	4	0.0000	0.178	0.0306	*Low*	52.09%	9.479%	6.446%
Inappropriate weather	**Scenario 1: High**										
Wind	W<3 32.59% W3~7 42.96% W>7 24.44%	0.9185	79.29	4	0.0000	0.459	0.4237	W>7	76.10%	51.66%	28.70%
Inappropriate weather	**Scenario 2: Medium**										
Wind	W<3 32.59% W3~7 42.96% W>7 24.44%	0.9185	79.29	4	0.0000	0.459	0.4237	W3~7	59.90%	16.93%	21.57%
Inappropriate weather	**Scenario 3: Low**										
Wind	W<3 32.59% W3~7 42.96% W>7 24.44%	0.9185	79.29	4	0.0000	0.459	0.4237	W<3	59.09%	26.49%	14.26%

The maximal variation of the significant direct factors, namely, 'equipment-related problems' and 'inappropriate surroundings conditions', as shown in the previous tests: the *Chi–square* χ^2 test, direct effect and the mutual information MI was calculated.

Performance of STR.16 could be 'perfect-work', 'acceptable-work' or 'defective-work'. When 'defective-work' was observed (i.e., the state of the quality output for executing STR.16 is defective-work), the model predicted that the probability of 'equipment-related problems' occurrence and 'inappropriate surroundings conditions' medium '*M*' increased. The maximal variation was 7.783% and 4.358% (positive variation) respectively (as shown in Table 8.18 and Figure 8.50 (a)). 'Equipment-related problems' and 'inappropriate surroundings conditions' are direct factors most prone to cause 'defective-work' in relation to STR.16.

When 'acceptable-work' was observed (i.e., the state of the quality output for executing STR.16 is acceptable-work), the model predicted that the probability of 'equipment-related problems' non-occurrence and 'inappropriate surroundings conditions' low '*L*' increased. The maximal variation was 4.104% and 0.722% (negative variation) respectively (as shown in Table 8.18 and Figure 8.50 (b)). 'Equipment-related problems' and 'inappropriate surroundings conditions' are direct factors less prone to cause 'acceptable-work'.

Similarly, when 'perfect-work' was observed (i.e., the state of the quality output for executing STR.16 is perfect-work), the model predicted that the probability of 'equipment-related problems' non-occurrence and 'inappropriate surroundings conditions' low '*L*' increased (negative variation). The maximal variation was 8.634% and 10.02% respectively (as shown in Table 8.18 and Figure 8.50 (c)). 'Equipment-related problems' and 'inappropriate surroundings conditions' are direct factor less prone to cause 'perfect-work'.



(a) Defective work (b) Acceptable work (c) Perfect work

Figure 8.50 *Maximal variation* of the direct factors of STR.16

8.3.5.2 First-level Causes of the Direct Factors 'Equipment-related Problems'

The independence tests *Chi–square* χ^2 show a significant association between 'hard to deal with equipment' with the 'equipment-related problems'; χ^2 (1) = 22.58, ($p<$ 0.05) (as shown in Table 8.18). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p>$ 0.05). The results support that only 'hard to deal with equipment' is significantly associated with 'equipment-related problems'.

'Hard to deal with equipment' was found have highest direct effect on direct factor 'equipment-related underperformance', at 0.497 (as shown in Figure 8.51). Also, MI amount of information brought by first-level causes 'hard to deal with equipment' to direct factor 'equipment-related underperformance' was *I*('hard to deal with equipment; 'equipment-related problems') = 0.1207 (as shown in Table 8.18 and Figure 8.49). 'Hard to deal with equipment' has the highest MI with 'equipment-related underperformance' indicating a more dependent relationship between the first-level causes and the direct factor.

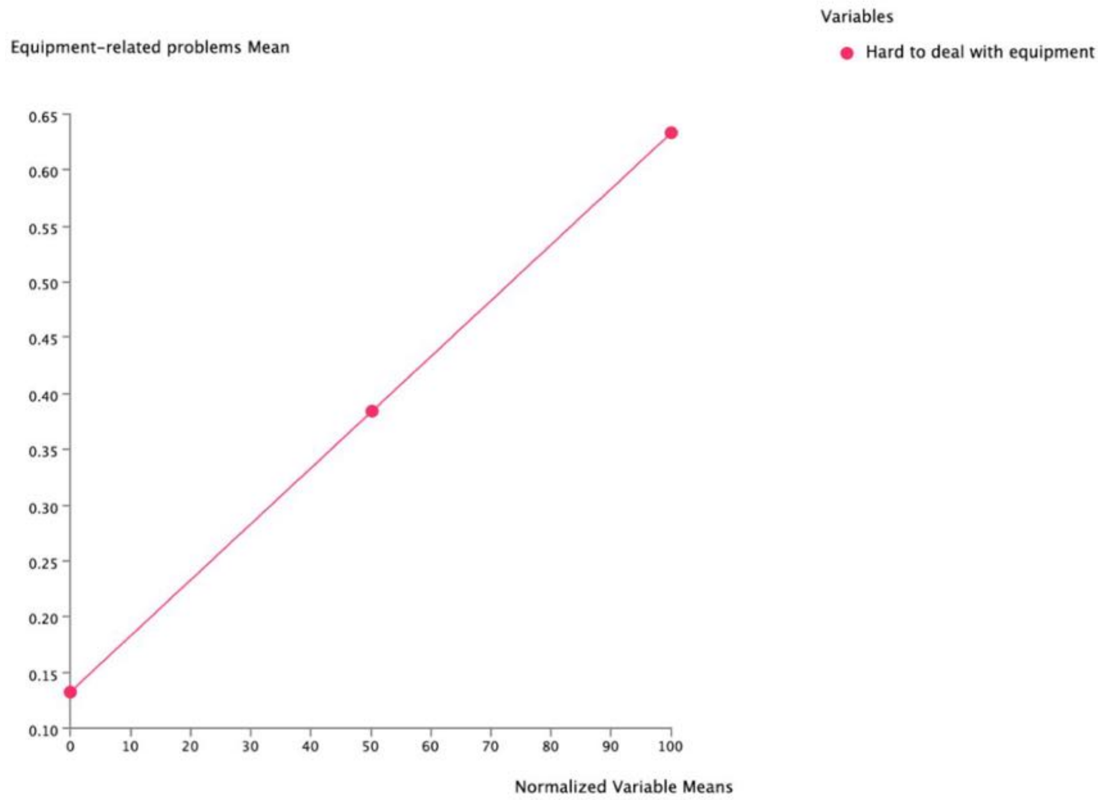
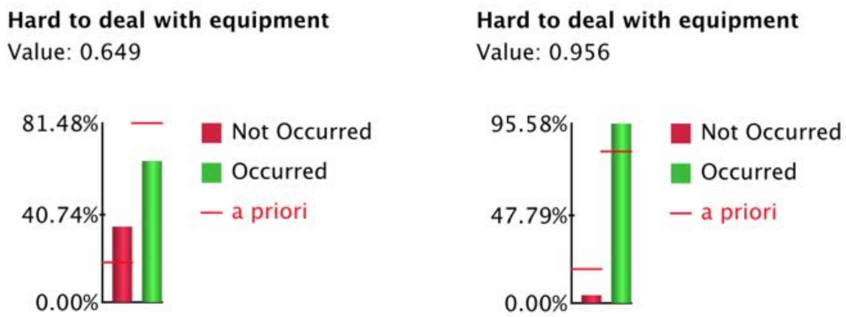


Figure 8.51 Direct effects of the potential causes of equipment-related problems

The maximal variation was determined for the significant first-level cause, namely, 'hard to deal with equipment'. The occurrence and non-occurrence of 'equipment-related underperformance' in relation to occurrence and non-occurrence 'hard to deal with equipment' was analyzed. When there is non-occurrence of 'equipment-related underperformance', the model predicts the probability of 'hard to deal with equipment' non-occurrence increases (as shown in Table 8.18). The maximal variation is 16.60% (negative variation) (as shown in Figure 8.52 (a)).

In contrast, when there is occurrence of 'equipment-related underperformance', the model predicts the probability of 'hard to deal with equipment' occurrence to increase. The maximal variation is 14.10% (positive variation) (as shown in Figure 8.52 (b)). 'Hard to deal with equipment' is the first-level cause most likely to underpin 'equipment-related underperformance'.



(a) Equipment-related problems: *Not occurred* (b) Equipment-related problems: *Occurred*

Figure 8.52 *Maximal variation* of hard to deal with equipment

8.3.5.3 First-level Causes of the Direct Factors 'Inappropriate Surroundings Conditions'

The independence tests *Chi–square* χ^2 show a significant association between 'inappropriate weather' with the 'inappropriate surroundings conditions'; χ^2 (4) = 90.97, ($p< 0.05$) (as shown in Table 8.18). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association ($p> 0.05$). The results support that only 'inappropriate weather' is significantly associated with 'inappropriate surroundings conditions'.

'Inappropriate weather' was found have highest direct effect on direct factor 'inappropriate surroundings conditions', at 0.178 (as shown in Figure 8.53). Also, MI amount of information brought by first-level causes 'inappropriate weather' to direct factor 'inappropriate surroundings conditions' was *I*('inappropriate weather'; 'inappropriate surroundings conditions') = 0.0306 (as shown in Table 8.18 and Figure 8.49). 'Inappropriate weather' has the highest MI with 'inappropriate surroundings conditions' indicating a more dependent relationship between the first-level causes and the direct factor.

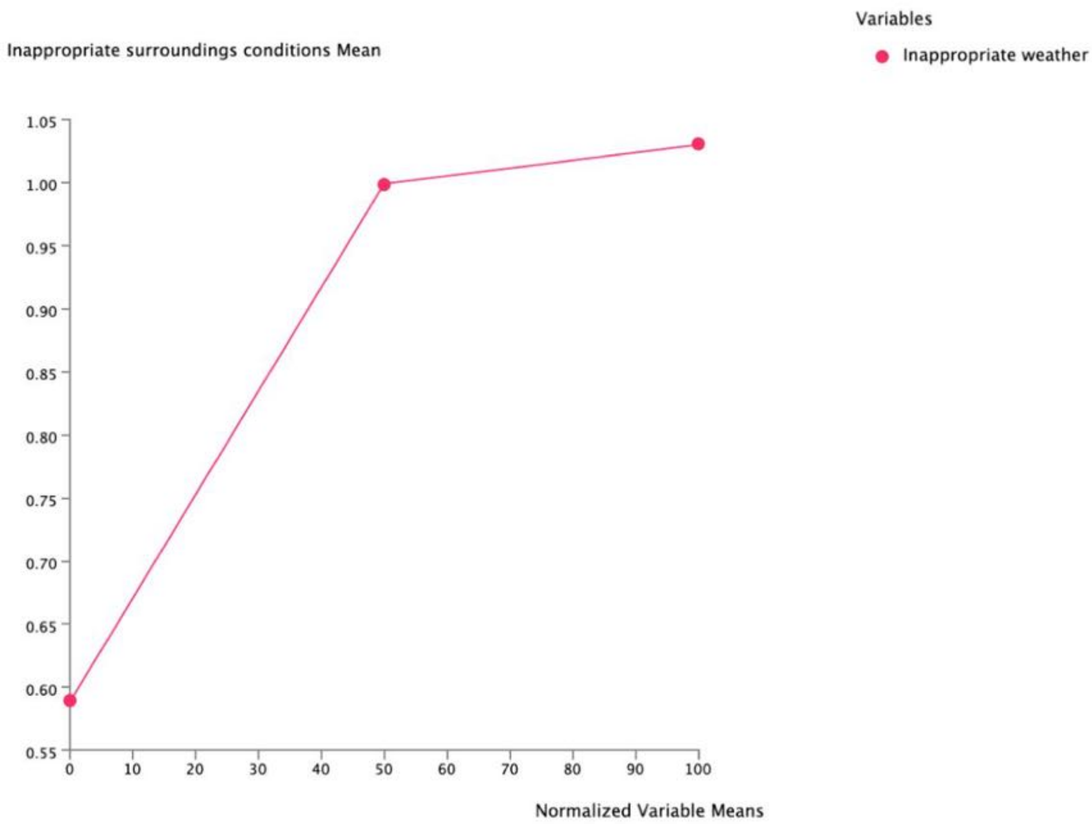
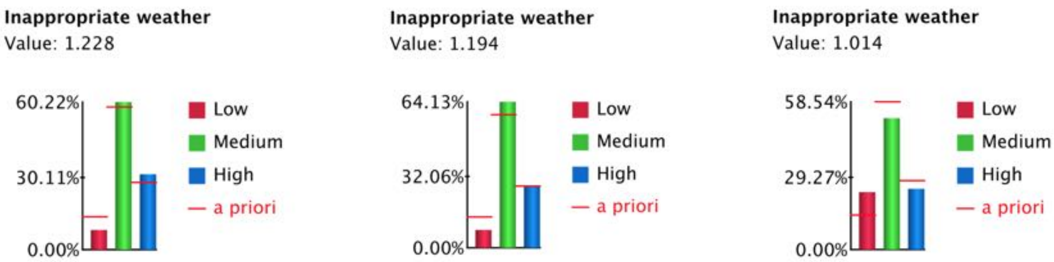


Figure 8.53 Direct effects of the potential causes of inappropriate surroundings conditions

The maximal variation was determined for the significant first-level cause, namely, 'inappropriate weather'. The occurrence and non-occurrence of 'inappropriate surroundings conditions' in relation to occurrence and non-occurrence 'inappropriate weather' was analyzed.

When there is '*high*' state of 'inappropriate surroundings conditions', the model predicts the probability of 'inappropriate weather' '*high*' increases (as shown in Table 8.18). The maximal variation is 3.577% (positive variation) (as shown in Figure 8.54 (a)). Similarly, when there is '*medium*' state of 'inappropriate surroundings conditions', the model predicts the probability of 'inappropriate weather' '*medium*' increases (as shown in Table 8.18). The maximal variation is 5.591% (positive variation) (as shown in Figure 8.54 (b)).

In contrast, when there is '*low*' state of 'inappropriate surroundings conditions', the model predicts the probability of 'inappropriate weather' '*low*' increases (as shown in Table 8.18). The maximal variation is 9.479% (negative variation) (as shown in Figure 8.54 (c)). ‘Inappropriate weather’ is the first-level cause most likely to underpin ‘inappropriate surroundings conditions’.



Inappropriate surroundings conditions:
(a) High (b) Medium (c) Low

Figure 8.54 *Maximal variation* of inappropriate weather

8.3.5.4 Second-level Causes of the First-level Cause ‘Inappropriate Weather’

The independence tests *Chi–square* χ^2 show a significant association between ‘inappropriate weather’ with the ‘wind’; χ^2 (4) = 79.29, (p< 0.05) (as shown in Table 8.18). The *Chi–square* χ^2 test results for the remaining direct factors failed to show a significant association (p> 0.05). The results support that only ‘wind’ is significantly associated with ‘inappropriate weather’.

‘Wind’ was found have highest direct effect on direct factor ‘inappropriate weather’, at 0.459 (as shown in Figure 8.55). Also, MI amount of information brought by second-level causes ‘wind’ to first-level causes ‘inappropriate weather’ was I(‘wind’; ‘inappropriate weather’) = 0.4237 (as shown in Table 8.18 and Figure 8.49). ‘Wind’ has the highest MI with ‘inappropriate weather’ indicating a more dependent relationship between the second-level causes and the first-level causes.

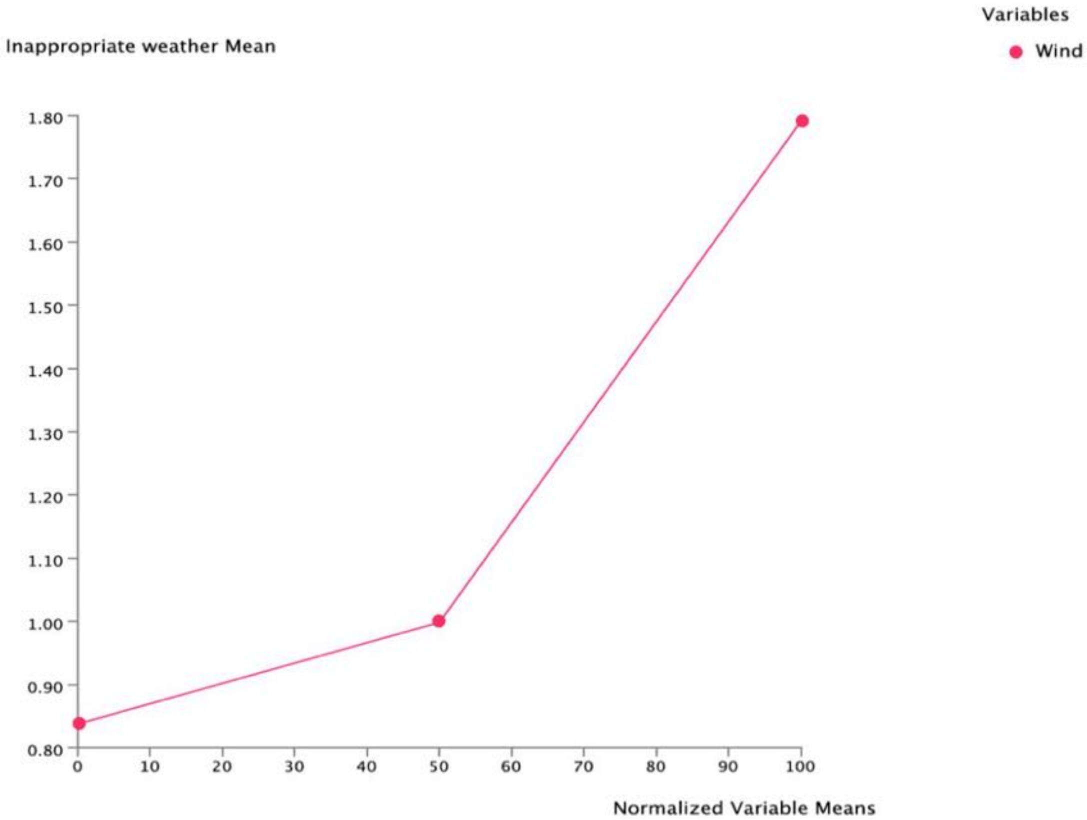
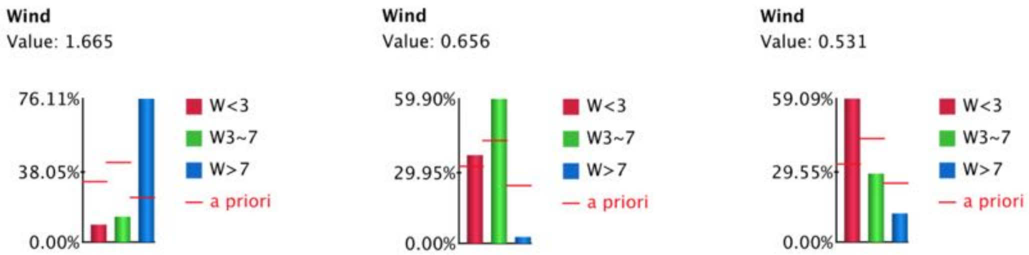


Figure 8.55 Direct effects of the potential causes of inappropriate weather

The maximal variation was determined for the significant second-level cause, namely, 'wind'. The occurrence and non-occurrence of 'inappropriate weather' in relation to occurrence and non-occurrence 'wind' was analyzed.

When there is '*high*' state of 'inappropriate weather', the model predicts the probability of 'wind' is '*W>7*' increases (as shown in Table 8.18). The maximal variation is 51.66% (positive variation) (as shown in Figure 8.56 (a)). Similarly, when there is '*medium*' state of 'inappropriate weather', the model predicts the probability of 'wind' is '*W3~7*' increases (as shown in Table 8.18). The maximal variation is 16.93% (positive variation) (as shown in Figure 8.56 (b)).

In contrast, when there is '*low*' state of 'inappropriate weather', the model predicts the probability of 'wind' is '*W<3*' increases (as shown in Table 8.18). The maximal variation is 26.49% (negative variation) (as shown in Figure 8.56 (c)). 'Wind' is the second-level cause most likely to underpin 'inappropriate weather'.



Inappropriate weather:

(a) High (b) Medium (c) Low

Figure 8.56 *Maximal variation* of wind

8.4 Model Validity

The following section discusses the examination of model validity and achievement of analytical generalisations with respect to the causal model proposed based on BBN. MMRE is a commonly applied equation to assess error rate in models (Foss, Stensrud, Kitchenham & Myrtveit, 2003). The prediction accuracy of a model can be calculated based on the MMRE value (see equation 8.1, 8.2 & 8.3).

Prediction accuracy:

$$Prediction\ accuracy = 1 - MMRE \tag{8.1}$$

Where

MMRE: Mean Magnitude of Relative Error

Mean Magnitude of Relative Error MMRE:

$$MMRE = \frac{1}{n}\sum_{i=1}^{n} MRE_i \tag{8.2}$$

Where

MRE: Magnitude of Relative Error

n: number of STRs

$i = 1, 2, 3, \ldots, n$

Magnitude of Relative Error MMRE:

$$MRE_i = \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8.3}$$

Where

y: First half

$\hat{y}$: Second half
i = 1, 2, 3, …, n

The MMRE and prediction accuracy are usually calculated following standard evaluation processes including cross-validation (Briand, El-Emam, & Wieczorek, 1999). An MMRE value of 0.25 or less is considered to be an acceptable value for the prediction of model accuracy (Conte, Dunsmore, & Shen, 1986). One advantage of determining MMRE is that researchers are able to make comparisons across data sets (Briand, Langley, & Wieczorek, 2000; Shepperd & Kadoda, 2001).

In this study, the researcher used the data sets presented in Chapter 4 to validate the proposed causal model. Using spilt-half approach, the STR data sets were divided into two groups with each group being constituted by approximately 50% of the original data set (Bollen, 2014; Drost, 2011; Nunnally, 1978), and then the data sets were entered into the BBN model and the results assessed. This predicted the maximal variation for number of significant factors found in each STR. Using MMRE values of the maximal variation between the two groups (after using spilt-half method and running the BBN model) enabled the researcher to be able to calculate the accuracy of the predictions. The following table, Table 19 provides the accuracy of the predictions for the five STRs.

Table 8.19 The accuracy of the model prediction for the five STRs

STRs		Test Re-Test for External Validity	
		Maximal Positive Variation	Maximal Negative Variation
STR.1	MMRE	8.11%	8.11%
	Prediction accuracy	91.89%	91.89%
STR.5	MMRE	6.78%	6.78%
	Prediction accuracy	93.22%	93.22%
STR.13	MMRE	6.36%	6.36%
	Prediction accuracy	93.64%	93.64%
STR.15	MMRE	13.44%	13.44%
	Prediction accuracy	86.55%	86.55%
STR.16	MMRE	15.26%	6.95%
	Prediction accuracy	84.74%	93.05%

As can be seen the MMRE for maximal variation generated from the model as determined by five STRs ranged from 6.36% to 15.26%. The range is within the threshold described by Conte et al (1986) and suggesting an acceptable range of values for the prediction of model accuracy. The prediction accuracy values for the maximal variation generated from the model as determined by five STRs were found to range between 84.74% and 93.64% suggesting satisfactory prediction accuracy. However, it is likely that a positive relationship exists between the prediction accuracy of the model and the sample size suggesting that the use of larger sample sizes in the future would further increase prediction accuracy.

The processes of applying the spilt-half method and running the BBN model with the two groups and attaining satisfactory prediction accuracy supports the validity of the model. An analytical generalisation that can be made is that the model can be used accurately with further and other STRs within the building code requirements in particular in residential construction projects.

8.4 Result Discussion

Through the investigation of the sensitivity of each STR towards quality deviation as presented in Chapter 5 and 6 together with measurement of the influence of direct factors of the sub-tasks and their causes as presented in this chapter this study provided a clear picture about different pattern of each STR in terms of their interaction. The results presented in this chapter show how the model identified the significant causes for each STR (STR.1, STR.5, STR.13, STR.15 and STR.16) and simulated and visualized each STR in terms of its interaction through graphical tools. The identification was made possible through structuring the process based on a review of related works in the literature, consideration of firsthand expert opinion, and applying a BBN analysis of data collected.

The interaction revealed a high level of complexity and uncertainty within each STR with varying levels STR to STR. The patterns for each STR become complex with increasing ambiguity due to the number of factors that can interact at the same time. Based on the distinction between which are the most significant causes of the interaction for the deviation of the quality practice for each STR, the results of this chapter identified the significant causes and in which STR such causes occurred. This is discussed in the following paragraphs.

As can be seen in Tables 8.15~8.17, ‘worker-related underperformance’ was observed and predicted as a quality deviation by the research model in STR.5 (Ties width: *D)*, STR.13 (Cross-sectional dimensions: width *x*) and STR.15 (Concrete cover *x)*. The primary contributing causes that are the first-level causes, to this case are ‘lack of knowledge’, ‘lack of commitment’ and ‘lack of skills’.

Concerning ‘lack of knowledge,’ it was found that 'dimensions required' was one essential contributing cause that is a second-level cause. The relationship was observed during investigation of STR.13 (see Table 8.16). Here, the consistency between the results and the literature is evident. Much has been written on the consequences of information scarcity and its impact on decision-making. Lopez et al. (2010) paraphrase Sunyoto and Minato's comments noting "errors committed of this nature arise from absent or faulty inferences for the correct information that is available." In this study, insufficient access to or understanding of the dimensions required was found to underpin poor performance. Kletz (1985) and Rasmussen (1983) note that knowledge-based errors are errors that arise unintentionally due to matter being beyond the capabilities of the individual. In other words, the individual may be dealing with a situation in which the he or she possesses incomplete knowledge, and therefore is unable to achieve an effective outcome.

In the study, observations frequently revealed a lack of knowledge and in particular a lack of awareness or understanding of the required dimensions to conduct the sub-task. Such was particularly noted during the execution of STR.13. The implication of this finding is that quality output can be improved through ensuring that workers have access to and understand the required parameters of tasks.

Concerning ‘lack of commitment’, it was found that ‘adherence to design and standard (SBC)’ and ‘adherence to procedures’ were essential contributing causes (second-level causes). The relationship was observed during investigation of STR.5, STR.13 and STR.15 (see Tables 8.15~8.17). Issues of adherence are often reported in the literature. While knowledge-based errors tend to arise largely non-intentionally, non-compliance with standards that are known tends to be somewhat underpinned by an intentional or reckless approach to tasks (Lopez et al., 2010).

Van-Dyck et al. (2005) associates non-compliance with violations, which they define as "intentional deviations from standards, norms, practices, or recommendations." The intentional nature of violations reflects potentially more serious issues within the organisation. Sunyoto and Minato (2003) in the context of occupational health and safety, define violations as "deliberate ... deviation from those practices deemed necessary to maintain the safe operation of a potentially hazardous system."

On site, it was observed that a number of workers refrained from achieving specific dimensions presented in project documentation, notwithstanding that they had previously indicated that they possessed the pre-requisite knowledge. This was particularly evident in relation to fabrication process of the ties for column cage (namely STR.5). There were related issues concerning 'Adherence to procedures', found to be another ‘lack of commitment’. A number of workers were found to ignore the task sequence during the fabrication stages of STR.5 and STR.15. Inconsistent machine setting in relation to STR.5 and inconsistent spacer operation in relation to STR.15 where found to were specific problems observed.

Concerning ‘lack of skills’, ‘work accurately’ and ‘handle with equipment’ were found to be essential contributing causes (second-level causes) as observed during investigations of STR.5, STR.13 and STR.15 (see Tables 8.15~8.17). Lopez et al. (2010) refer to "skill-based errors" as errors, which arise, from an acceptable plan, but actions not being performed as planned. Cheyne et al. (2006) referred to this category of errors as "execution deviations" as the error arises due to a departure from the plan. Skill-based errors, in this sense, are largely unintentional errors. On site, it was observed that a significant number of workers, did not possess sufficient skills to achieve the required dimensions accurately as mentioned in the project documentations notwithstanding that these workers had been found to have the required knowledge and be highly committed to executing tasks adhering to design standards and endorsed procedures. The issue was observed during investigations of STR.5, STR.13 and STR.15. Similarly, a number of workers were observed as appearing to lack the skills to handle with equipment. The issue was particular acute in relation to manual devices and those machines relevant to achieving the required dimensions. The issue was observed in relation to STR.5 and STR.15.

‘Supervisor-related underperformance’ was observed and predicted as a quality deviation by the research model in STR.1 [Steel cross-section area (A_{st})] (see Tables 8.2). ‘Lack of commitment’ of the supervisor performance (see Table 8.12) was found to a primary contributing cause (a first-level cause). Supervisor ‘absenteeism’ was found to be an essential contributing cause (a second-level cause) to such ‘lack of commitment’ (see table 8.14). Aljassmi, H., et al. (2013) notes that it is most typically the field supervisor’s responsibility to filter information discrepancies, errors and misinterpretations during the construction stage of a project. Yet Silva, Ruwanpura and Hewage (2009) and Aljassmi, H., et al. (2013) present reports that 30% of field supervisor’s time was found wasted on ineffective activities or absenteeism from their job. The condition that violations typically proliferate in environments where there is poor supervision is without contention (Reason, 2002; Van-Dyck et al., 2005).

Supervisor absenteeism was one of the second-level causes has been predicted by the model based on observation of STR.1. Such absenteeism was more often observed in relation to the private residential projects (namely villas) more than apartment residential projects. The supervisory pattern for the private residential projects is often temporary with an inspector visiting the site regularly. In contrast, apartment residential projects tend to have a permanent supervisor in the form of inspector or inspector team on site. The intermittent nature of supervision in private residential projects means that often the inspector will pay most attention to quality once the construction stage is complete a time which is often too late to check STR performance. This is particular true for STR.1.

‘Materials-related problems’ was observed and predicted as a quality deviation by the research model in STR.1 (see Table 8.2). ‘Inadequate quantity of material’ was found to be a primary contributing cause (a first-level causes) (see Table 8.4). Inadequate quantity of material is an issue, which can arise often due to due poor planning. Based on observations of STR.1, the model predicted inadequate quantity of material had a significant relationship with quality deviation. On site, it was found that material shortages led a number of workers to undertake compensatory actions such as reducing the number of bars per column cage. Such actions would have led to a reduction in the required steel ratio for those columns.

‘Equipment-related problems’ was observed and predicted as a quality deviation by the research model in STR.5, STR.15 and STR.16 (see Tables 8.15, 8.17 and 8.18). ‘Hard to deal with equipment’ and ‘equipment availability’ were found to be primary contributing causes (as first-level causes). Tserng et al., (2013) found that ineffective use of machines and equipment accounted for 15% of total project waste in the construction sector.

‘Equipment availability’ issues, such as equipment shortage, were observed particularly in relation to STR.15. On site, it was found that a shortage of concrete cover spacers led to reduced concrete cover of columns and contraventions of building code requirements and project documentation. Another 'equipment-related problems’ issue stems from the equipment itself. During observations of STR.5 and STR.16 it was noted that there was a tendency to rely on traditional tools such as a ‘Plumbob’, to construct a true vertical alignment of the columns. Such tools tended to have an inherent susceptibility to inaccuracy, which led to deviation from acceptable ranges.

'Documentation-related underperformance’ was observed and predicted as a quality deviation by the research model in STR.1 (see Table 8.6). ‘Specifications-related underperformance’ and ‘drawings-related underperformance’ were found to be primary contributing causes (first-level causes) (see table 8.6). In relation to 'drawings-related underperformance', ‘wrong information’ was found to be an essential contributing cause (second-level cause) (see table 8.8 and 8.10). Oyewobi et al., (2011) reporting on studies in Nigeria reveal that specifications and drawings relevant to construction projects commonly contain errors, inconsistencies, and omissions, and also commonly lack clarity. There is also a risk of the passing on of wrong information and that end users of such documents will ignore or neglect even the correct contents of such documents. Josephson & Hummarlund (1999) found that misleading design-related information was a prime determinant of defect occurrence. In this study, ‘Documentation-related underperformance’ was found to impact significantly on STR.1 but not others suggesting that STR.1 is more sensitive to the information the other STRs and that the nature of information of STR.1 might be more difficult to settings by the designers.

The 'Inappropriate surroundings conditions' was observed and predicted as a quality deviation by the research model in STR.16 (see Table 8.18). 'Inappropriate weather' was found to be a primary contributing cause (a first-level cause) (see table 8.18). In relation to 'inappropriate weather', 'wind' was found to be an essential contributing cause (a second-level cause) to condition. Such was observed during investigation of STR.16 (see table 8.18). Wind together with noise, site conditions, external interference and even political and social instability are often tied to adverse task completion (Fayek et al., 2003; Liu & Li, 2012; Love et al. 1997). On site, it was observed that increases in wind speed appeared to be a likely condition impacting on the verticality setting of columns due to the impact of the wind on the tools used.

8.5 Suggestions and Recommendations

The literature to date has investigated quality deviation, construction defects and causation in terms of defect type, building element, activity or task. The limitation of studies to date particularly those concerned with concrete building structures is the depth of analysis. A focus on the requirements of sub-tasks and relationships with quality deviation (adopted here) has thus far been an approach that has been largely neglected. This study contributes to knowledge in the field of defect control by investigating the relevance of the requirements of sub-tasks. The study also contributes to the area through reporting on the application of a BBN approach to quality deviation approach. Together a model is proposed which offers a means to predict causes of quality deviation for each STR.

Findings from this research are patterns inherent for each STR. STR.1 *[quality lack-of compliance relative to steel cross-section area (A_{st})]* has three direct factors ('documentation-related underperformance', 'materials-related problems' and 'supervisor-related underperformance') driven by four first-level causes ('specifications-related underperformance', 'drawings-related underperformance', 'inadequate quantity of material' and 'lack of commitment') that themselves are driven by second-level causes (such as 'wrong information' from the specifications, 'wrong information' from the drawings, and the supervisor 'absenteeism'). The cause patterns are STR specific. The implication is that each STR must be investigated in isolation and cause patterns cannot be generalised. In other words, the findings of this study emphasize the importance of checking cause patterns for each STR separately to be able to control the potential causes for each STR.

The results suggest that Quality Practitioners, in particular, Quality Control Managers and Building Site Inspectors, should prioritize for the most significant causes of quality deviation for each STR as a means of improving the inspection process. Such an approach would also aid in the design of protection and proactive strategies to manage undesirable quality practices.

The capacity to visualize the causation paths of quality deviation is another contribution of this study. Visualization of causation could be adopted as an inspection tool through quality control software based on the development of a wide database of STRs relevant to building construction. Added value could arise from further research simulating STR patterns and the development of an augmented reality platform. The upshot would be solutions to aid the prevention of quality deviations and construction defects though proactive actions based on the history of each STR.

8.6 Conclusions

This chapter is an extension for previous work on chapters 5 and 6. The BBN approach was utilized to quantify the most significant causes through observing and predicting of the interaction between the deviation level in terms of the quality practices for each STR (five STRs have been examined: STR.1, STR.5, STR.13, STR.15 and STR.16) and which kind of causes that related to each STR. Based on the statistical examinations and metrics, the significant causes for five different STRs have been identified using data set includes 135 events (site measurements, direct observations, auditing the project documentations and structural interviews) for each STR from 27 case studies from construction residential projects. The quality deviation causes for each STR have divided into three levels: the direct factors (i.e., task resources and task surroundings conditions) include the 6 direct factors (e.g., ‘workers’); first-level causes include the 6 causes (e.g., workers ‘knowledge’) and finally second-level causes include the 41 causes (e.g., knowledge about the ‘required dimensions’).

The study shows different patterns among STRs that indicates that it is highly ill-advised to deal with all STRs as same manner. In particular, it is impractical to generalise the causes for each STR to the other. So, the study recommends that the identification model developed here be used to establish the causes for each respective STR (quality non-compliance) that potentially leads to quality deviation in order to control the potential causes and improve the quality practices for each sub-task requirement. Such an approach shall greatly assist Quality Managers and Building Inspectors to detect implicit prevention and proactive strategies to help control quality deviation and defect through prioritisation of the most significant causes for each STR in order to improve overall quality and inspection systems. Indeed the results here contribute greatly to visualisation techniques able to clarify the causal paths of any subsequent quality deviation. This strategy, if adopted as an inspection tool by quality control software throughout the building can be argued to ultimately add value to databases cumulatively, and subsequently include all sub-task requirements applicable across all types of construction projects.

CHAPTER 9: Conclusion

9.1 Research Overview

A large body of research points to the fact that in the construction industry; in particular, residential buildings suffer from quality deviation and construction defects. Quality management interventions do appear to be increasingly applied in such projects, however barriers to the uptake of these methods and techniques exist (Jaafari, 1996; Chileshe, 1996; Bubshait & Al-Atiq, 1999; Love, Mandal & Li, 1999; Love, Li, Irani & Holt, 2000; Pheng & Toe, 2004; Haupt et al., 2004; Turk, 2006). One of these barriers relates to understanding the sensitivity patterns of (sub)tasks (involved in the project) to deviation, in particular, there is a need to better understand quality deviation from the requirements of sub-tasks and their respective relationship with direct causes of deviation. Indeed industry has real initiatives for simulation of the actual practices of quality attainment across project sites, especially if inspection processes are to be targeted and effective and efficient.

Quality deviation as a result of non-compliance with project design specifications and building codes during building-work and resultant on-site construction defects in as-built components, leads to rework (and capital budget and schedule overruns), and life-cycle maintenance concerns (at the post certificate-of-completion stage) (Azhar et al., 2011; Love et al., 2013). Rework of failing building elements stems largely from deviations from quality procedures (Lopez et al., 2010; Vlassis et al., 2007). Reducing quality deviation is a critical focal point for genuine improvement of the construction industry and in particular residential projects.

For at least the past decade and a half, scholars have become interested in the optimal adoption of quality management interventions in the construction industry. Studies published relate to quality deviation analysis, defect occurrence and rework. A number of frameworks have been developed to improve the quality management in construction industry and quality control in particular. However, to date, there is a dearth of studies focusing on the nature of the (sub)tasks of construction. In particular, there has been a severe lack of emphasis in consideration of the impact of building code requirements and the relationships of these requirements with direct causes of deviation. To bridge the gap, the research objectives of this project aimed to understand and simulate the actual practices of quality-attainment at the sub-task level. The conceptual framework and the factors used in this research build upon prevailing theoretical understandings within the field.

The main aim of the study was to develop an approach to determine patterns of quality deviation and defect occurrence in the construction industry using a novel quality deviation classification system and novel mode to simulate interactions between deviations of STRs and direct causes. To address the primary aim, six objectives were formulated and pursued. The achievement of the six objectives is described in the following chapter. In addition the academic and practical contributions of the research project are described as are the specific limitations of the project. Finally, directions for areas of future investigation in the field are provided.

9.2 Achievements of Objectives

Objective one: *To identify factors relevant to quality deviation and defect occurrence in the construction industry through a review of the literature*.

Factors relevant to quality deviation and defect occurrence were identified based on the task resource and workplace conditions. Based on a review of the literature related to quality deviation and defect occurrence, an initial draft list of 87 items was determined. Prior empirical studies in this regard have focused on either direct or root causes, rework or consequences, the modeling and prediction techniques, and the quality practices. The items were tested for content validity involving three judgments by a panel of three experts. The final list of the factors was reduced into 65 items based on objective analysis of expert opinion.

Objective two: *To measure susceptibility to deviation for individual STRs to determine whether isolated STRs exhibit unique deviation patterns*.

In particular, the study explored the nature and pattern of tasks (pursuant to building code requirements) and each task's susceptibility to deviation by dividing work-site activities into sub-tasks. To address this objective, the design specifications for specific sub-tasks from requirements from building codes (e.g. SBC and ACI) and project documentation (e.g. drawings, specifications) were identified and these parameters were used to set target measurements, tolerance range and maximum/minimum boundaries for each sub-task. These points were used to measure deviation degree.

To address the objective, CPI analysis, a statistical process control tool, was applied to determine the capability of a process C_p and C_{pk}. Here, the susceptibility of each STR to exposure to quality deviation was identified and statistical process control amounts C_p and C_{pk} were employed to measure quality practices for 17 STRs respectively across 27 separate construction sites.

The study found that the susceptibility of each STR to deviation varies with the complexity or difficulty of meeting the requirements for the sub-task. The implication is that each task should be broken down in to sub-tasks and consideration given to specific requirements of the sub-task, in order for accurate analysis of quality deviation and construction defects.

The CPI technique showed that 23.5% of STRs showed less susceptibility to deviation

> [namely: *STR.1, STR.6, STR.9 and STR.11, representing sub-tasks of achieving and installing Steel cross-section area (A_{st}); Ties depth; Ties: Bend dimensions; and Vertical spacing between ties, were less likely to result in knock-on structural column sub-defects*].

On the other hand 41% of STRswere more likely to exceed the specification limits (STR.3, STR.7, STR.8, STR.12, STR.13, STR.14 and STR.15);

While the remaining 35.3% of STRs showed higher susceptibility to deviation.

[*in other words STR.2, STR.4, STR.5, STR.10, STR.16 and STR.17, representing the sub-tasks of achieving and installing Longitudinal Bars Length; Offset bars - longitudinal bars; Ties width; Horizontal spacing between longitudinal bars; Deviation from plumb for column: Column levelling; and, Deviation between horizontal elements in column, all showed a high propensity for quality deviation away from expected quality-norms for the finished structural column*].

The implication is that task characteristics dictate the susceptibility of each STR to exposure to quality deviations. The majority of STRs were found to have low C_{pk} values due to central deviation from the pre-sets.

Complexity, difficulty, item size, constraining tolerance limits were some of the characteristics of STR that affected incidence of quality deviations. Column dimension STRs, for example, have tight constraining limits and were found to have higher incidence of deviation. Relationships between different STRs also influences quality practices and can cause more severe risk for some STRs. Insufficient technical awareness of design codes and other requirements of sub-tasks amongst non-technical staff also caused deviation risk in the representative structural column, and by extension risk of failure to the facility generally.

The implication is that inspection work cannot be exerted equally across STRs without regard to the complexity of STR relationships, the personnel level of understanding of pre-set requirements and offset from tolerance limits even where the C_p value is higher. The distribution of inspection effort should take into account STR complexity, sub-task risk severity, STR relationships, C_p value, and the influence of the specific STR on project budgeting and time constraints.

Objective three: *To classify each STR based on its tendency to be performed across six novel classes*.

The classification of tasks into micro-level manageable STRs was expected to produce a clearer picture about the deviation patterns of the STRs. The expectation was that such information would be useful to ensuring appropriate allocation of inspection effort to minimise deviation occurrence.

To address this third objective, an anatomical analysis for each STR was conducted to present its quality performance. The classification included distribution based on the relationship between STR and deviation class; distribution based on the expected quality output i.e., perfect-work, acceptable-work or defective-work output; and, distribution based on sources of deviations and defects. The frequency of occurrence of each of the six classes was determined and used to assist understanding patterns of deviation occurrence.

In relation to the relationship between STR and deviation class, acceptable-work deviation during actual work (the execution phase) was the most common occurrence (56.3%). Defective-work during actual work (the execution phase) (24.7%) followed. Perfect-work had an occurrence of 16.9%. The other classes were found to have very low occurrence (0.1-1.0%).

In relation to the expected output works for STRs, acceptable-work constituted over half of the cases (57.3%). Defective-work constituted approximately a quarter of cases (25.7%), and perfect-work recorded the lowest ratio (16.9%).

Finally in relation to deviation sources by STR, “actual” (the execution phase) source dominated the majority of cases (81.1%). “No deviation” was recorded at 16.9%. The "actual and design” source was recorded to be around 1.90%, and the ratio of the "design” source only was 0.1%.

Most STRs were prone to deviation. Across 17 STRs the sensitivity towards deviation classes was found to vary, especially for those classes related to actual work (the execution phase). The six-class approach to classification contributes to the body of defect management knowledge by providing a quantitative framework platform for researchers to apply to future investigations into accurate defect analysis; and moreover also contribute to (better) practice on-site, through providing a means to assess deviation occurrence and source of deviation occurrence, and inform the allocation of inspection effort towards most efficient and effective best-practice for such building inspections.

Objective four: *To measure and rank the sensitivity towards each class from one STR across all STRs.*

The objective of measuring association between degree of deviation and STRs, and ranking the sensitivity towards each class from one STR across STRs was intended to provide information concerning the level of variation and sensitivity between the STRs.

To address the study objectives, the data set was analyzed by chi-square ($\chi 2$) statistical analysis and odds ratio testing. Chi-Square ($\chi 2$) analysis was used to determine association between degree of deviation and the STRs. The odds ratio test is the measurement of the ratio between the odds of the presence of a certain quality deviation from a particular task or sub-task and the odds of the absence of that specific quality deviation. The odds ratio test is often used to evaluate the ratio between odds of an outcome occurring to the odds of it not occurring. In this research, odds ratio analysis was used to rank sensitivity degree of STRs.

In relation to the relationship between STR and deviation class, Chi-Square ($\chi 2$) test indicated a low to medium association. The general pattern of this class for STRs is one of predominant independence. Having said this, isolated STRs were found to have atypical frequencies of classes, which may suggest a need for higher caution when dealing with these tasks.

In relation to expected output works for STRs, Chi-Square ($\chi 2$) test indicated a medium to high association suggesting a statistically significant association between degree of deviation and STRs. Although, the general pattern of the degree of deviation; i.e. perfect, acceptable or defective; for STRs is one of predominant dependence, some may deviate and demand greater attention from inspectors.

In relation to deviation sources by STR, Chi-Square ($\chi 2$) test indicated a low to medium association. The general pattern of the deviation sources for STRs is predominantly independent. Caution is required when dealing with these tasks as isolated STRs were found to have atypical frequencies of classes.

In relation to odds ratio values, the deviation sensitivity variation of STRs towards perfect-work, acceptable-work and defective-work was measured with STR.17 taken as benchmark. The majority of STRs were more sensitive to the "perfect-work" criteria than the benchmark. STR.6 and STR.14 (*Ties depth achievement and Cross-sectional dimensions: formwork depth as sub-tasks of structural column installation*) were particularly prone to classification as "perfect-work". In contrast, the majority of STRs were less sensitive to "acceptable-work" criteria compared to the benchmark. STR.9 and STR.11 however, were more prone to classification as "acceptable-work" than the benchmark. Similarly most STRs were more sensitive to the "defective-work" criteria than the benchmark. STR.3 and STR.12 (*lap splices and Spacing above the slab as sub-tasks in the installation of structural columns*) were particularly prone to classification as "defective-work". Again, the results support that the nature of each STR differs in terms of its sensitivity to quality deviation.

Designers should take the variation in sensitivity to quality deviation STR to STR into consideration in order to develop appropriate design and performance of each STR. Similarly, an awareness of variation in sensitivity to quality deviation STR to STR would help to inform proactive strategies to minimise deviation occurrence.

Objective five: *To develop and test a novel BBN-based model capable of simulating realistic interaction of quality deviation with its causes at the STR level.*

It was anticipated that a novel model based on BBN (developed here) would be a useful tool to simulate interaction between quality deviation with causes of deviation. The model was intended to be able to determine the variation of influence of direct causes of deviation affecting each STR.

To address the fifth objective, earlier work (described in Chapters 5 and 6) was extended upon. A BBN approach was used to quantify the most significant causes of deviation through observing and predicting interaction between the deviation level in terms of the quality practices for 5 STRs (STR.1, STR.5, STR.13, STR.15 and STR.16 were examined) and which causes of deviation related to deviation for each STR.

Unique causation patterns of deviation were identified for each STR. The result supports that a STR-by-STR approach would be the most efficient approach to defect management. To date, cause patterns for individual STRs have been neglected. Scholars have considered causes of deviation on a presumption that the causes affect tasks uniformly. In other words, a one-cause-pattern-fits-all approach has been applied. The results in this study emphasize the importance of checking cause patterns for each STR separately to be able to control potential causes of deviation appropriately for each STR.

Deviation in STR.1 (*the sub-task of achieveing and installing compliant steel cross-section areas*) was found to be underpinned by three direct factors ('documentation-related underperformance', 'materials-related problems' and 'supervisor-related underperformance') driven by four first-level causes ('specifications-related underperformance', 'drawings-related underperformance', 'inadequate quantity of material' and 'lack of commitment') that in turn are underpinned by second-level causes ('wrong information' from the specifications, 'wrong information' from the drawings, and the supervisor 'absenteeism').

Deviation in STR.5 (*achieving compliant tie-widths for structural columns*) was found to be underpinned by different direct factors. Deviation in STR.5 was also found to be underpinned by a pattern of direct factors that was different from the patterns that caused deviation in other STRs (STR.13, STR.15 and STR.16). The results support that QC processes should be designed so that the treatment of the most significant causes of quality deviation for each STR is prioritized.

The results support that as the influence of particular causes of deviation vary STR to STR, effectiveness in defect management may be lost where a non-STR-specific approach to QC management is used. The results support the identification of deviation cause patterns for each STR involved in a construction project. Where specific STRs are prone to deviation due to causes specific to those STRs, the defect management approach should reflect such.

Objective six: *To provide recommendations with respect to the nature of STRs in concrete structural construction and model quality deviation and defects.*

The following discussion addresses objective six, namely the development of recommendations towards appropriate for sub-task quality-compliance(s) for structural concrete construction.

Recommendation-1: The variation in sensitivity to quality deviation STR to STR should be considered during the design and the implementation of each STR. During the design stage, an understanding of this variation should inform the design of defect management strategies so that interventions to reduce sources of major deviation can be prioritized and redundant interventions eliminated. During the implementation stage, an understanding of this variation should inform the relative amount of caution that should be applied. STRs more prone to deviation should be tended to with greater care.

Recommendation-2: Inspection effort (for on-site building activities) cannot be exerted equally across STRs without regard to the nature of STRs and the STRs' sensitivity to deviation. Inspection effort should be designed and distributed based on the sensitivity of the relevant STRs to deviation. So, there is *no* specific benefit to be gained from conducting *uniform* inspection procedures, that is, no benefit in applying the same inspection effort, across all STRs. Site inspectors can be advised explicitly of comparatively lower or higher susceptibilities (potential respective exposure) to deviation. For example, C_p values for tie depth (STR.6) can be expected to hit target whereas C_p values for rebar lap splicing (STR.3) generally fall to satisfy requirements. Resultantly to achieve the desired quality control for columns, an inspector should allocate more time resources to rebar splicing, and less to tie depth preparations.

Recommendation-3: As the patterns of direct causes of deviation are unique for each STR, each STR should be investigated in isolation. Cause patterns cannot be generalised. By understanding cause patterns for each STR, quality managers will be able to apply a more targeted approach to defect control.

Recommendation-4: Quality managers should use a visualization tool to clarify the STR-specific cause of deviation pathways. A database of STRs applied in the construction sector should be developed. Such a resource would add value to quality practices through providing a base for further research into the simulation of STR patterns. An augmented reality platform should be developed. Such a development would enable a sophisticated approach to defect management. Specifically, the history of each STR in terms of its proneness to deviation and the causes of deviation most influential to it would be available to inform best practice.

Generalizations-1: This study identifies unique patterns for each STR indicating that it is illogical to deal with all STRs in the same manner. In particular, the generalization of the causes of deviation for one STR to another must be avoided. The study was conducted in Saudi Arabia suggesting that the findings can only be generalized to this setting. Similarly, the generalisability is limited to the specific 17 STRs examined across the 27 building sites visted.

Generalizations-2: The study implies that deviation pattern of all or even groups of STRs in the construction industry cannot be generalized. In this study, none of the STRs investigated had the same quality deviation sensitivity. The result highlights the need for defect management researchers to focus on the STR level in order to generate meaningful representations of the likelihood of defect occurrence.

Generalizations-3: Statistical generalizations related to direct causes of deviation (for STR.1, STR.5, STR.13, STR.15 and STR.16) in projects in Saudi Arabia are provided. Such generalisations should improve QC processes and inspection performance through providing meaningful information concerning deviation patterns and direct causes of deviation for each of the 5 STRs.

Generalizations-4: Theoretical generalizations related to the proposed and developed model are provided. The model can be adopted for future research efforts in different countries. The model can used to study different parts of building structures or different phases of construction project delivery, such as the design phase.

9.3 Contributions to the Knowledge

9.3.1 Theoretical benefit and contributions to existing body of knowledge

The study provides a number of theoretical benefits.

1. The study provides an introduction on the use of SPC analysis to assess STR deviation. SPC analysis is a common quality management tool applied in manufacture. However, the study has shown its application as a QC tool in construction by adopting SPC analysis for the evaluation of 17 STRs related to columns. The specific SPC applied depends on the fundamental requirement of the relevant building code.
2. The study proves sensitivity towards quality deviation varies STR to STR. The finding supports the need to investigate proneness to the quality deviation and construction defects on a STR level.
3. The six-class classification approach contributes to the body of defect-occurrence knowledge by providing a platform for researchers to model future investigations into accurate defect analysis. The classification approach proposed and tested by the study provides a means to gather insight about each STR based on its tendency to be performed across six novel classes.
4. The study introduces a novel approach to simulating the actual practice of quality and direct causes of deviation using BBN. The model links the degree of deviation for each STR with its direct causes. The direct effect and MI between the degree of deviation for each STR (perfect, acceptable or defective-work) and the direct causes is also able to be calculated using the proposed model. Also, the direct effect and MI between the direct causes and the first and second level of causes can also be calculated.
5. The study proves the direct causes between STRs are different from each other. The result adds value to the body of knowledge through emphasizing the need to use an anatomical approach to investigate the causes of quality deviation.

9.3.2 Industrial contribution and benefit

1. The study identifies which causes of quality deviation (and non-compliance) for each (activity sub-task) STR are most likely to lead to actual deviation. The finding serves to assist Quality Managers to better understand the potential causes of deviation STR to STR. Such information would aid the detection of implicit prevention and proactive strategies to control deviation through prioritizing focus on the most significant causes of deviation for each STR.
2. The study proposes and tests a novel simulation capable of simulating actual practices onsite. The model is suitable for industry application for the purposes of STR deviation cause prediction across different elements of building structures. The proposed model is suitable for future linkage with infrared or point cloud technology systems to streamline inspection.

9.3.4 Implications for the quality practices in residential projects in Saudi Arabia

1. Context-specific findings were that quality practices for a number of STRs were poor. The practice of STR.1, the steel cross-section area "A_{st}" of longitudinal bars for the column was found to be particularly hazardous potentially leading to the production of unsafe buildings and catastrophic collapse. More attention into quality practices is required especially in relation to the more risky STRs identified.
2. Overall the causes of quality deviation for the five STRs were different. For example, project documentation appeared to a unique issue for STR.1. Notwithstanding this, worker performance and equipment-related factors tended to be present as direct causes of quality deviations at least to some extent across the five STRs. This finding is consistent with other studies into the construction sector in Saudi Arabia and suggests the need to particular attention to be devoted to these issues.

9.4 Limitations

The study focused on only one structural (concrete column) sub-element of a typical residential building. Thus, the results of the study are limited to the structural element investigated. Similarly, due to practical constraints the study focused on only 17 STRs when theoretically there are a vast number of possible STRs that could have been investigated. In other words, the study was only able to investigate a relatively small proportion of the total number of STRs that could be relevant to the construction of a building. Other STRs related to the column element and STRs related to different structural elements of the construction building such as the slaps, walls and so on, were not examined. Notwithstanding this, the number of events (n= 3030) observed on-site and in-person by the researcher for the selected STRs goes some way to mitigating the narrow scope of the study.

Another limitation is that the study was only able to provide a representation of the quality practices in residential construction in Saudi Arabia. As each country has its own legal compliance requirements and policy in relation to minimum acceptable levels of quality practices. Each country also has different entry-level requirements for construction personnel and different levels of tolerance to deviation from explicit standards. Any generalization of the results of this study to construction practices in other countries must be done so with considerable caution. While the context-specific nature of the findings is an important limitation concerning the generalizability of the findings of the study it is also an opportunity for comparable studies to be conducted in orders to valid the phenomenon globally.

The researcher drew the applied direct causes from a review of the literature and through input from industry experts. While the researcher was keen to identify the most important direct causes of deviation and also to include a wide range of causes of deviation, it is inevitable that some causes of deviation in construction may have been unintentionally omitted from the analysis or unintentionally misrepresented.

Defect management to date is a field of knowledge in which there are a range of theoretical frameworks and these frameworks rely on different semantics to convey meaning. It is also possible that there are context-specific causes of deviation not expressly noted in the literature and not necessarily within the knowledge of industrial experts, and therefore not included in the study.

Finally, while the study provides insight into the construction elements and task activities in terms of their sub-task sensitivity to deviation, it is vital that inspection is not abandoned in the cases of relatively low sensitivity to deviation. Specifically, in a minority of cases inspection remains vital even where C_p values are high (such as confirmation of steel cross-section-areas, STR.1). Other parameters must be factored-in, in order to gather a more complete picture of the extent of risk related to the performance of particular STRs. The degree of risk severity will be related to the specific sub-tasks' position on a critical-path. Specific sub-tasks will have a higher supply-cost than others. The work-method involved for each sub-task will be different. These additional factors influencing the degree of risk severity were not considered in this study and therefore represent an important limitation that needs to be taken into consideration.

9.5 Areas for Future Research

The study provides foundation for a number of future investigations. In this study, the data was collected and analysed from the concrete column structural component of the building. The sensitivity of STRs derived from other structural components also needs to be investigated. Such a study would serve as a useful comparative investigation and inform the generalisability of the findings of both studies. Similarly, the investigation in this study was limited to residential buildings in Saudi Arabia. It is important for a similar investigation to be conducted in other contexts. As construction tends to a setting-specific activity, such future studies would serve to inform the generalisability of the findings of both studies.

The study identified the existence of interdependencies between STRs. For example, exceeding the maximum requirements of the tie dimension (width and depth) can affect the dimensions of concrete cover, which might increase the probability of deviation from the acceptable minimum limits for the dimensions of concrete cover(s). There is a need to further investigate the interdependencies of STRs or a broader scale.

As mentioned, while the study provides insight into the construction elements and task activities in terms of their sub-task sensitivity to deviation, other parameters must be factored-in. Future work that would add value to this study, and draw value from this study, would be calculation of the potential risks (the degree of risk severity) for each STR. The degree of risk severity could relate to cost or time issues or other factors related to the client satisfaction. Such an investigation would help to identify the most important STRs to be focused on during the inspection process; in other words, not only would the Building-Inspector be aware of the likelihood of deviation but also the consequence; and indeed extend this towards an integrative model addressing all parameters for a more thorough BBN approach.

The proposed model currently only focuses on simulating direct causes of deviation with quality practice output (perfect-work, acceptable-work and defective-work). A more comprehensive picture may be obtainable through linking the direct causes of deviation to root causes of deviation. Such an approach may serve to provide the construction industry with even more workable recommendation for defect management. Indeed important for future study is the willingness to link relationships between STRs in terms of sequential deviation and interdependency of their requirements. Such an approach would again offer a more realistic representation of the degree of risk severity from STR to STR.

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APPENDIXES

Appendix A

Inspection Checklist (direct measurement)

	Date: ……/……./ 2013				Column 1		Column 2		Column 3		Column 4		Column 5	
	Project number#				Design	Actual	Design	Actual	Design	Actual	Design	Actual	Design	Actual
Rebar	**Longitudinal Bars Fab.**	**STR.1**	Steel cross-section area (A_{st})											
		STR.2	Bars Length: designed length *x*											
		STR.3	Lap splices											
		STR.4	Bars Offset - longitudinal bars											
	Ties & Hooks	**STR.5**	Ties width: *D*											
		STR.6	Ties depth: *d*											
		STR.7	Ties: Hooks dimensions	Side.1										
				Side.2										
		STR.8	Ties/Hooks Angular °											
		STR.9	Bend Diameter [D], Bar $\phi = x$											
	Cage Assembling	**STR.10**	Horizontal [clear] spacing *x*	Max										
				Min										
		STR.11	Vertical [clear] spacing x_v	Max										
				Min										
		STR.12	Spacing above the slab *x*											
Formwork	**Formwork Shuttering**	**STR.13**	Cross-sectional dimensions: width *x*											
		STR.14	Cross-sectional dimensions: depth *x*											
		STR.15	Concrete cover *x*	Side.1										
				Side.2										
				Side.3										
				Side.4										
	Formwork leveling	**STR.16**	Deviation from plumb for column *x*											
	Column positioning	**STR.17**	Deviation between horizontal items	Side.1										
				Side.2										

Appendix B

Structured interview and observation schedule

	Factors and Variables of the Quality Deviation			
	XB. Task Resource Factors			Score
	1	XB.1. Worker-related underperformance *Has STR deviation been caused by worker-related underperformance?*		*Yes/No*
Structured interview		2	XB.1.1. Lack of Knowledge Factors *Has STR deviation been caused by worker lack of knowledge?*	*Yes/No*
		3	XB.1.1.1. Material size/type *Is there a worker lack of knowledge about material size/type?*	*Yes/No*
		4	XB.1.1.2. Material quantity *Is there a worker lack of knowledge about material quantity?*	*Yes/No*
		5	XB.1.1.3. Dimensions required *Is there a worker lack of knowledge about dimensions?*	*Yes/No*
		6	XB.1.1.4. Tolerance required *Is there a worker lack of knowledge about tolerance permitted?*	*Yes/No*
		7	XB.1.3. Experience *How many years has the worker been employed as a tradesperson?*	*……… Years*
Observation		8	XB.1.2. Commitment *Has STR deviation been caused by worker lack of commitment?*	*Yes/No*
		9	XB.1.2.2. Communication with supervisor *Does the worker exhibit a lack of commitment towards communication with supervisor?*	*Yes/No*
		10	XB.1.2.3. Adherence to procedures *Does the worker exhibit a lack of commitment towards procedures?*	*Yes/No*
		11	XB.1.2.4. Adherence to design & standard (SBC) *Does the worker exhibit a lack of commitment towards design & standards (SBC)?*	*Yes/No*
		12	XB.1.2.5. Teamwork *Does the worker exhibit a lack of commitment towards teamwork?*	*Yes/No*
Observation		13	XB.1.4. Skills *Has STR deviation been caused by worker lack of skills?*	*Yes/No*
		14	XB.1.4.1. Communication *Does the worker lack communication skills?*	*Yes/No*
		15	XB.1.4.2. Material/equipment handling *Does the worker lack skills concerning the handling of materials/equipment?*	*Yes/No*
		16	XB.1.4.3. Understanding of information *Does the worker lack skills concerning dealing with information?*	*Yes/No*
		17	XB.1.4.6. Working accurately *Does the worker lack precision?*	*Yes/No*
	18	XB.2. Supervisor-related underperformance *Has STR deviation been caused by supervisor performance?*		*Yes/No*
Structured interview		19	XB.2.1. Knowledge *Has STR deviation been caused by supervisor lack of knowledge?*	*Yes/No*
		20	XB.2.1.1. Material size/type *Is there a supervisor lack of knowledge about material size/type?*	*Yes/No*
		21	XB.2.1.2. Material quantity *Is there a supervisor lack of knowledge about material quantity?*	*Yes/No*
		22	XB.2.1.3. Dimensions required *Is there a supervisor lack of knowledge about dimensions?*	*Yes/No*
		23	XB.2.1.4. Dimensions tolerance *Is there a supervisor lack of knowledge about tolerance permitted?*	*Yes/No*

		24	XB.2.3. Experience *How many years has the supervisor been employed in a quality manager/inspector role?*	*………Years*
Observation		25	XB.2.2. Commitment *Has STR deviation been caused by supervisor lack of commitment?*	*Yes/No*
		26	XB.2.2.2. Communication with labors *Does the supervisor exhibit a lack of commitment towards communication with workers?*	*Yes/No*
		27	XB.2.2.3. Adherence to procedures (No omission) *Does the supervisor exhibit a lack of commitment towards procedures?*	*Yes/No*
		28	XB.2.2.4. Adherence to design & standard (SBC) *Does the worker exhibit a lack of commitment towards design & standard (SBC)?*	*Yes/No*
		29	XB.2.2.5. Excessive supervisory absenteeism *Does the worker exhibit a lack of commitment towards personal attendance?*	*Yes/No*
Observation		30	XB.2.4. Lack of management and skills *Does the deviation of the STR might be caused by the lack of skills of the supervisory?*	*Yes/No*
		31	XB.2.4.1. Communication *Does the supervisor lack communication skills?*	*Yes/No*
		32	XB.2.4.2. Understanding of information *Does the supervisor lack skills for dealing with information?*	*Yes/No*
		33	XB.2.4.3. Handle with Documents/Resources *Does the supervisor lack skills concerning the management of documents/resources?*	*Yes/No*
		34	XB.2.4.5. Working accurately *Does the supervisor work accurately?*	*Yes/No*
	35	XB.3. Materials-related underperformance *Has STR deviation been caused by materials-related underperformance?*		*Yes/No*
Observation		36	XB.3.1. Materials availability *Is material shortage observed?*	*Yes/No*
		37	XB.3.2. Inadequate quantity of material *Is the quantity of materials insufficient?*	*Yes/No*
		38	XB.3.3. Noncompliance with specifications *Is specification non-compliance observed?*	*Yes/No*
		39	XB.3.4. Hard to deal with material *Is the material selected for use appropriate for the task?*	*Yes/No*
	40	XB.4. Equipment-related underperformance *Has STR deviation been caused by equipment?*		*Yes/No*
Observation		41	XB.4.1. Equipment availability *Is equipment shortage observed?*	*Yes/No*
		42	XB.4.2. Inadequate quantity of equipment *Is the quantity of equipment insufficient?*	*Yes/No*
		43	XB.4.3. Noncompliance with specifications *Is specification non-compliance observed?*	*Yes/No*
		44	XB.4.4. Hard to deal with equipment *Is the material selected for use appropriate for the task?*	*Yes/No*
	45	XB.5. Documentation-related underperformance *Has STR deviation been caused by documentation-related underperformance?*		*Yes/No*
Gathering the design information		46	XB.5.1. Drawings *Has STR deviation been caused by project drawings?*	*Yes/No*
		47	XB.5.1.1. Missing Information *Do project drawings omit information?*	*Yes/No*
		48	XB.5.1.2. Misleading Statements *Do project drawings contain misleading statements?*	*Yes/No*
		49	XB.5.1.3. Wrong Information *Do project drawings contain incorrect information?*	*Yes/No*
		50	XB.5.1.4. Unavailable documentation *Is any project documentation unavailable?*	*Yes/No*

Gathering the design information		51	XB.5.2. Specification *Has STR deviation been caused by specification-related problems?*	*Yes/No*
		52	XB.5.2.1. Missing Information *Do specifications omit information?*	*Yes/No*
		53	XB.5.2.2. Misleading statements *Do specifications contain misleading statements?*	*Yes/No*
		54	XB.5.2.3. Wrong Information *Do specifications contain incorrect information?*	*Yes/No*
		55	XB.5.2.4. Unavailable documentations *Is any specification unavailable?*	*Yes/No*
	56	**XC. Task Surroundings** *Has STR deviation been caused by surroundings conditions?*		*H/M/L*
Observation		57	XC.1. Weather and Environment Factors *Has STR deviation been caused by the weather?*	*H/M/L*
		58	XC.1.1. Hot/Cold (Temperature) *What is the temperature?*	……… C^0
		59	XC.1.2. Rain *What is the precipitation?*	*Yes/No*
		60	XC.1.3. Wind *What is the wind speed?*	……… *m/s*
Observation		61	XC.2. Site Condition Factors (Working environment) *Has STR deviation been the site condition factors?*	*Yes/No*
		62	XC.2.1. Crowd, Traffic, Dust & Noise *Is there any crowd, traffic, dust & noise?*	*Yes/No*
		63	XC.2.2. Access to work location *Is there any difficulty related to access to work location?*	*Yes/No*
		64	XC.2.3. Unforeseen ground–site conditions *Is there any unforeseen ground–site conditions?*	*Yes/No*
		65	XC.2.4. External Uncertainty *Is there any external uncertainty?*	*Yes/No*

Appendix C

Content validity

Content validity questions	Recommendations	M
1. To what extent do you agree that the present factors and variables reflect the real practices of the in-site construction?	**Interview.1** = 3 **Interview.2** = 4 **Interview.3** = 5	3 + 4 + 5 = 12 12/15 = **4**
2. To what extent do you agree that the present factors and variables comprehensive? And fundamental items have been addressed?	**Interview.1** = 3 **Interview.2** = 5 **Interview.3** = 5	3 + 5 + 5 = 13 13/15 = **4.33**
3. To what extent do you agree that the present factors and variables able to measure the causes of defective acts during execution task?	**Interview.1** = 5 **Interview.2** = 4 **Interview.3** = 3	3 + 4 + 5 = 12 12/15 = **4**
4. Do you think that the present factors and variables able to measure the causes of defective acts during execution task (precondition factors and variables)?	**Interview.1:** *Yes*. **Interview.2:** *Yes*. **Interview.3:** *Yes*.	
5. Do you think that some of the present factors and variables need to remove? *Kindly list these factors and variables:*	**Interview.1:** *Yes*. **Interview.2:** *Yes*. **Interview.3:** *Yes*.	
6. Do you think that some of the present factors and variables need to modify? *Kindly list these factors and variables:*	**Interview.1:** *No*. **Interview.2:** *No*. **Interview.3:** *No*.	
7. Do you think that some of the present factors and variables need to add? *Kindly list these factors and variables:*	**Interview.1:** *No*. **Interview.2:** I think the list is comprehensive for its intended purpose. **Interview.3:** *No*.	

Appendix D

Model validity - STR.1

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.1 = D Documentation-related underperformance	23.04%	21.73%	5.709%
STR.1 = D Materials-related problems	12.48%	10.47%	16.075%
STR.1 = D Supervisor-related underperformance	12.03%	9.80%	18.586%
STR.1 = A Documentation-related underperformance	16.43%	14.58%	11.235%
STR.1 = A Materials-related problems	8.86%	7.07%	20.191%
STR.1 = A Supervisor-related underperformance	2.17%	2.05%	5.388%
STR.1 = P Documentation-related underperformance	0.19%	0.18%	8.080%
STR.1 = P Materials-related problems	6.24%	5.32%	14.839%
STR.1 = P Supervisor-related underperformance	2.43%	2.36%	2.887%
Materials-related problems = Not Occurred Inadequate quantity of material	11.39%	10.59%	6.986%
Materials-related problems = Occurred Inadequate quantity of material	27.27%	27.65%	1.399%
Supervisor-related underperformance = Not Occurred Lack of commitment	0.76%	0.65%	14.147%
Supervisor-related underperformance = Occurred Lack of commitment	35.62%	32.68%	8.238%
Lack of commitment = Not Occurred Absenteeism	6.26%	5.85%	6.512%
Lack of commitment = Occurred Absenteeism	19.50%	19.08%	2.147%
Documentation-related underperformance = Occurred Specifications-related underperformance	11.05%	10.84%	1.834%
Documentation-related underperformance = Occurred Drawings-related underperformance	6.51%	6.03%	7.346%
Documentation-related underperformance = Not Occurred Specifications-related underperformance	12.44%	11.84%	4.817%
Documentation-related underperformance = Not Occurred Drawings-related underperformance	7.32%	6.58%	10.161%
Specifications-related underperformance = Not Occurred Wrong Information	5.84%	5.44%	6.850%
Specifications-related underperformance = Occurred Wrong Information	19.63%	19.36%	1.373%
Drawings-related underperformance = Not Occurred Wrong Information	9.78%	8.85%	9.529%
Drawings-related underperformance = Occurred Wrong Information	37.23%	38.05%	2.215%
		Σ MRE	**186.52%**
		n	**23**
		MMRE	**8.11%**
		1-MMRE	**91.89%**

Model validity - STR.5

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.5 = D Worker-related underperformance	5.96%	5.92%	0.613%
STR.5 = D Equipment-related problems	7.87%	7.92%	0.673%
STR.5 = A Worker-related underperformance	7.59%	7.68%	1.308%
STR.5 = A Equipment-related problems	0.97%	0.93%	4.426%
STR.5 = P Worker-related underperformance	2.80%	2.99%	7.078%
STR.5 = P Equipment-related problems	8.62%	8.59%	0.351%
Equipment-related problems = Not Occurred Hard to deal with equipment	7.82%	6.85%	12.318%
Equipment-related problems = Occurred Hard to deal with equipment	7.43%	7.25%	2.413%
Worker-related underperformance = Not Occurred Lack of commitment	21.72%	21.30%	1.932%
Worker-related underperformance = Not Occurred Lack of skills	16.01%	14.89%	6.957%
Worker-related underperformance = Occurred Lack of commitment	3.87%	3.71%	4.062%
Worker-related underperformance = Occurred Lack of skills	2.85%	2.59%	8.978%
Lack of commitment = Not Occurred Adherence to design & standard (SBC)	15.09%	13.47%	10.786%
Lack of commitment = Not Occurred Adherence to procedures	4.18%	3.02%	27.793%
Lack of commitment = Occurred Adherence to design & standard (SBC)	28.02%	26.01%	7.173%
Lack of commitment = Occurred Adherence to procedures	7.76%	5.83%	24.870%
Lack of skills = Not Occurred Work Accurately	14.33%	15.22%	6.223%
Lack of skills = Not Occurred Handle with material/equipment	6.72%	7.02%	4.478%
Lack of skills = Occurred Work Accurately	12.65%	12.96%	2.411%
Lack of skills = Occurred Handle with material/equipment	5.93%	5.98%	0.728%
		Σ MRE	**135.57%**
		n	**20**
		MMRE	**6.78%**
		1-MMRE	**93.22%**

Model validity - STR.13

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.13 = D Worker-related underperformance	9.49%	8.68%	8.523%
STR.13 = A Worker-related underperformance	5.58%	4.99%	10.551%
STR.13 = P Worker-related underperformance	5.83%	5.23%	10.299%
Worker-related underperformance = Not Occurred Lack of skills	3.74%	3.72%	0.367%
Worker-related underperformance = Not Occurred Lack of commitment	2.59%	2.52%	2.784%
Worker-related underperformance = Not Occurred Lack of knowledge	1.51%	1.42%	6.166%
Worker-related underperformance = Occurred Lack of skills	15.81%	17.51%	10.793%
Worker-related underperformance = Occurred Lack of commitment	10.97%	11.86%	8.103%
Worker-related underperformance = Occurred Lack of knowledge	6.39%	6.67%	4.349%
Lack of knowledge = Not Occurred Dimensions required	9.61%	9.33%	2.925%
Lack of knowledge = Occurred Dimensions required	9.79%	10.32%	5.364%
Lack of commitment = Not Occurred Adherence to design & standard (SBC)	3.66%	3.84%	4.932%
Lack of commitment = Occurred Adherence to design & standard (SBC)	6.38%	6.81%	6.644%
Lack of skills = Not Occurred Work Accurately	35.76%	32.27%	9.758%
Lack of skills = Occurred Work Accurately	9.81%	9.43%	3.917%
		Σ MRE	**95.47%**
		n	**15**
		MMRE	**6.36%**
		1-MMRE	**93.64%**

Model validity - STR.15

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.15 = D Equipment-related problems	15.52%	12.22%	21.24
STR.15 = D Worker-related underperformance	7.07%	6.29%	10.98
STR.15 = A Equipment-related problems	12.29%	14.91%	21.23
STR.15 = A Worker-related underperformance	0.62%	0.75%	20.33
STR.15 = P Worker-related underperformance	6.13%	5.20%	15.23
STR.15 = P Equipment-related problems	4.47%	4.94%	10.62
Equipment-related problems = Not Occurred Equipment availability	9.61%	11.63%	21.03
Equipment-related problems = Occurred Equipment availability	12.70%	14.90%	17.31
Worker-related underperformance = Not Occurred Lack of skills	5.15%	4.93%	4.21
Worker-related underperformance = Occurred Lack of skills	23.97%	25.86%	7.92
Lack of skills = Not Occurred Work Accurately	9.58%	8.53%	10.98
Lack of skills = Occurred Work Accurately	11.16%	11.13%	0.27
		Σ MRE	**161.334**
		n	**12**
		MMRE	**13.444**
		1-MMRE	**86.555**

Model validity - STR.16: Positive Maximal Variation

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.16 = D Equipment-related problems	14.46%	13.61%	5.868%
STR.16 = D Inappropriate surroundings conditions	6.29%	6.39%	1.573%
STR.16 = A Equipment-related problems	10.83%	8.90%	17.818%
STR.16 = A Inappropriate surroundings conditions	5.86%	3.99%	31.928%
STR.16 = P Equipment-related problems	16.09%	14.89%	7.471%
STR.16 = P Inappropriate surroundings conditions	9.65%	9.37%	2.904%
Equipment-related problems = Not Occurred Hard to deal with equipment	18.00%	15.45%	14.183%
Equipment-related problems = Occurred Hard to deal with equipment	14.43%	13.23%	8.292%
Inappropriate surroundings conditions = High Inappropriate weather	3.99%	4.00%	0.130%
Inappropriate surroundings conditions = Medium Inappropriate weather	6.16%	10.95%	77.744%
Inappropriate surroundings conditions = Low Inappropriate weather	10.92%	6.16%	43.611%
Inappropriate weather = High Wind	43.87%	43.70%	0.382%
Inappropriate weather = Medium Wind	13.77%	13.89%	0.845%
Inappropriate weather = Low Wind	17.24%	17.38%	0.860%
		Σ MRE	**213.61%**
		n	**14**
		MMRE	**15.26%**
		1-MMRE	**84.74%**

Model validity - STR.16: Negative Minimal Variation

	Test y	Re-Test ŷ	MRE = |(y- ŷ)/y|
STR.16 = D Equipment-related problems	14.46%	13.61%	5.868%
STR.16 = D Inappropriate surroundings conditions	8.31%	7.59%	8.642%
STR.16 = A Equipment-related problems	10.83%	8.90%	17.818%
STR.16 = A Inappropriate surroundings conditions	7.21%	6.53%	9.372%
STR.16 = P Equipment-related problems	16.09%	14.89%	7.471%
STR.16 = P Inappropriate surroundings conditions	5.34%	4.93%	7.719%
Equipment-related problems = Not Occurred Hard to deal with equipment	18.00%	15.45%	14.183%
Equipment-related problems = Occurred Hard to deal with equipment	14.43%	13.23%	8.292%
Inappropriate surroundings conditions = High Inappropriate weather	6.33%	6.35%	0.321%
Inappropriate surroundings conditions = Medium Inappropriate weather	6.61%	7.22%	9.178%
Inappropriate surroundings conditions = Low Inappropriate weather	7.21%	6.63%	8.055%
Inappropriate weather = High Wind	21.95%	21.96%	0.053%
Inappropriate weather = Medium Wind	19.82%	19.80%	0.102%
Inappropriate weather = Low Wind	9.52%	9.54%	0.256%
		Σ MRE	**97.33%**
		n	**14**
		MMRE	**6.95%**
		1-MMRE	**93.05%**