IDENTIFICATION OF CONSTRUCTION PROJECT PROBLEMS AND THEIR IMPACTS ON PROJECT SUCCESS

By

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To my family;
Keun Ho Kim, Kye Haeng Jo, Won Sook Kim, and Won Jae Kim

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By

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The traditionally accepted success parameters for construction projects are mainly cost and schedule. There are new trends in how to define success and the number of success parameters considered even though cost and schedule are still the most prevalent ones. The number and priority of success parameters heavily depends on the owner. With respect to these trends, determining the success of project is a hard and complicated procedure when a project faces multiple problems simultaneously. The problems that practitioners or researchers face are: 1) What are the relationships between these causes and their impacts on project success parameters?; 2) Is it necessary to concern all problems for each different project success parameter in terms of their negative impacts?; and 3) What problem is really considered when, especially, the project has more than one success parameter with different priorities? The proposed solutions are 1) to determine the relationships between problems and their impacts and 2) to select problems required to be considered for each project success parameter to meet multi-project success parameters within different priorities. This will help ensure that the project meets the required performance targets and adds value for all participants at the early phase of

project. Confirmatory factor analysis (CFA) models were used for testing the quality of proposed solutions. The outputs of CFA were used for an application tool to select the most critical problems under given circumstances such as parameter priorities and problems severity. A single multi-attribute rating technique using swing (SMART*S*) was the statistical tool used for this study. The results of this research show the selection of critical problem groups under given circumstances. In the future contractors, owners, and other project participants can use this technique to more effectively conduct project reviews during the course of the project.

CHAPTER 1
INTRODUCTION

With respect to the development of technologies and new demands on markets, many things in the construction industry have been changing rapidly and some new trends have emerged. It appears impossible for the construction industry to break free from these current trends. These trends would be the changes in the contract types, the development of technologies and methodologies to manage the project problems effectively, and new demands from owners (customers) on project outcomes. For example, even though, the highway industry has used the lowest bid system for a long time, new innovative methods in contracting such as 'Method A+B' and 'Lane Rental' have been proposed and/or are replacing the lowest/competitive bid (Herbsman et al. 1995; Herbsman and Ellis 1992). A similar situation could be easily found in commercial construction as well. There are many computer software programs available that make construction management easier and more effective than ever before. Owners' requests on projects have diversified as compared to the past. Owners may not share the same concepts of project success parameters such as cost and schedule any longer. The success of a project heavily depends on the owner's requirement. Apparently there are concerns other than just cost and schedule in terms of project success parameters from an owner's perspective. To keep their business rolling, it is critical for contractors to meet owners' demands on projects in our rapidly changing industry.

One of the keys to meeting owners' demands is to manage the project problems a contractor faces or will face in the near future because there exist probable relationships between owners' demands and problems in affecting the success of a project success as defined by the owner. Regarding the type of problems impeding success on construction projects, there are prospectively two main questions. The first question is "What kinds of problems exist on

projects?" The second is "How do they differ from the problems of a few years ago?" The answer to the first question could include material delays, the qualification of subcontractors and architects, request for information (RFIs), and change order, etc. The answer to the second question would be "No." Unlike new trends and changes in demands, it does not appear that the types of construction project problems have been changed that much. Nowadays, contractors must manage multiple problems simultaneously.

The traditional project success parameters are cost and schedule. As mentioned above, however, there are new, additional success parameters as defined and prioritized by the owner. The new project success parameters could vary among projects and their owners. These new parameters might be narrowed down to safety, quality, and owner's satisfaction. It is apparent that any project in the immediate or near future has more than one or two success parameters. There are numerous articles and abundant research available on project success parameters and/or key performance indicators. This research addresses the fact that different problems have different impacts on success parameters. But unfortunately it does not fully explain the difference. There are two types of variables involved in this research and they are independent and dependent variables. Although the project success index is represented as a dependent variable, it is hard to define "success (success index)" because success is a combination of different parameters (Griffith et al. 1999). Some dependent variables such as quality, safety, and satisfaction are not available and/or easily accessible to researcher. These kinds of variables are treated as confidential (safety incident rates and related indices) in a company and it is hard to measure the degree of agreement (quality and safety). Therefore, the current studies and research lack multi-project success parameters. Most studies have focused on cost and schedule by predicting the outcomes during the course of project. Even though a predicted outcome may

give a guideline of how to manage the project at that moment, it does not specify where to improve or fix the problems if the predicted outcome is not good. And also there are many problems, factors, and indicators addressed without looking at their impacts on the project success parameters.

This research is focused on finding the practices of general contractors and owners to improve project performance during project execution. These practices could provide additional insight into the success parameters while complimenting current approaches. This will help ensure that the project meets the required performance targets and adds value for all participants at an early stage of a project. The primary beneficiaries of this research include owners, contractors, and other project participants.

Problem Statement

The problem statement is:

How much could project performance have been improved if the relationships between problems and success parameters had been pre-identified in situations where there are multi-project success parameters each with different priorities?

Research Questions

Five research questions have been developed for this research effort. These questions must be investigated to address the research problem. The questions identified are as follows:

- What are the common problems on projects?
- What are the relationships between problems and their impacts on project success parameters?
- How different are these relationships when project success parameters have different priorities?
- How can critical problems be identified under given circumstances of multiple success parameters and different priorities?

- How can intangible variables (parameters) be measured in practice?

Purpose, Objectives, and Approach

The main purpose of this research is to identify best practices to improve project performance through the analysis of impacts of the problems on a project on project success parameters. To achieve the purpose of this research, the objectives should be identified. The objectives are: 1) Establish a definition of project success parameter; 2) Determine frequent problems and their causes in projects; 3) Identify correlations between problems within each success parameter; 4) Determine all possible significant relationships that affect project success parameters and problems types; and 5) Determine how intangible variables (parameters) could be measured. Figure 1-1 shows the overall approach of this research.

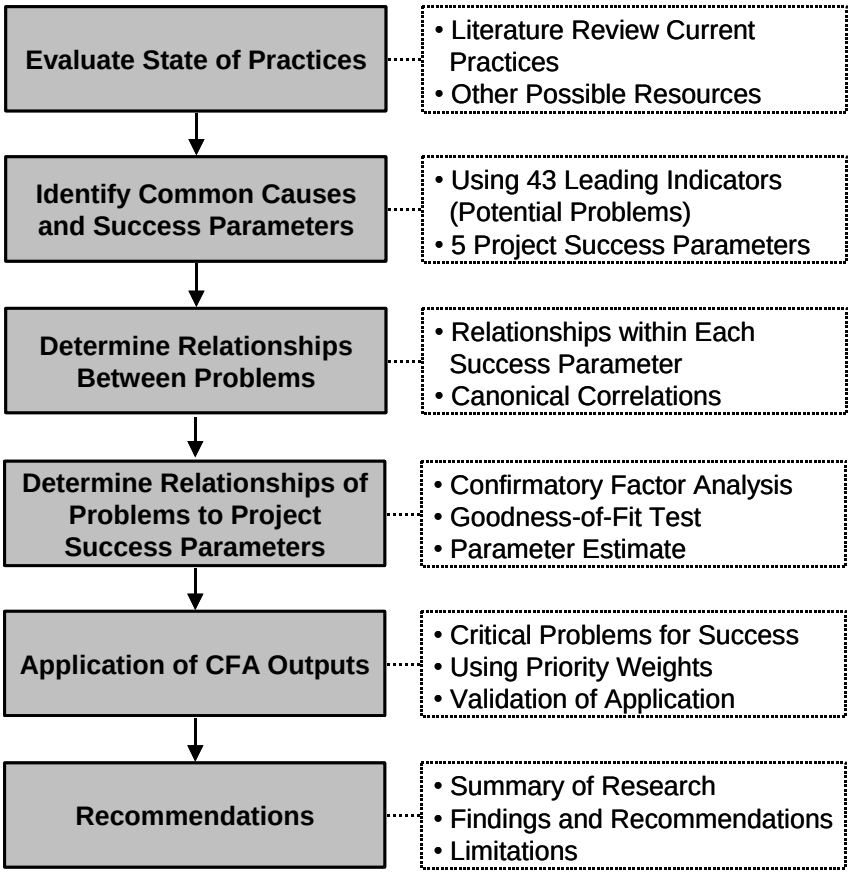


Figure 1-1. Research approach

Layout of Dissertation

Chapter 2 of this report provides an overview and additional background information on this research. The review of current literature is presented. Chapter 3 describes the strategy and design of this research. This includes an overview of the research approach and a development of relationships between problems. A description of the data collection process and a discussion of the data analysis are presented. Finally the research methodology will be discussed. Chapter 4 presents the general procedure of factor analysis for both exploratory and confirmatory analysis and their results and findings of the study. Chapter 5 provides the development of an application of outputs for reassessment of potential project problems. This includes an overview, application, and validation of the methodology. Chapter 6 provides conclusions and then recommendations for the usage of the methodology.

CHAPTER 2
LITERATURE REVIEW

Overview

To set up the framework of the research, a review was conducted of other research, current trends, related topics, and methodologies. Although a literature review is the first step of this research, it is very hard to find the same or at least similar topics or subjects among current research. Some of the main concerns are performance/key indicators/factors in general construction management and the process of how to develop performance indicators and how to measure them by looking for success parameters. Project control, major issue areas, and how to measure project performances will be discussed. This chapter mainly consists of three sections. One is about the development of project success criteria and another is about the project performance measure, and the last is about weights in index modeling. In addition to the main sections, there will be a brief discussion on decision-making theory which may apply to the development of an application for this research. More detailed information will follow.

Project Success Factors/Criteria

Factors Affecting the Success of a Construction Project

Chan et al. (2004) addressed the number of factors affecting a construction project. The study of previously successful projects and their critical success factors (CFSs) is a step toward determining means to improve the effectiveness of projects. However the concept of project success has remained ambiguously defined in the mind of construction professionals. The researcher reviewed current journals, sorted out the success factors (CFS) for construction projects from their case studies, and finally categorized them into five groups. The five groups are: Project Management Actions, Project Procedures, External Environment, Project-Related Factors, and Human-Related Factors. The Human-Related factors group has the largest number,

22, of factors and the Project Procedures has the lowest number, two. The External Environment has six factors, which are 1) Economic environment; 2) Social environment; 3) Political environment; 4) Physical environment; 5) Industrial relations environment; and 6) Technologically advanced. Figure 2-1 shows the five groups each with its set of factors.

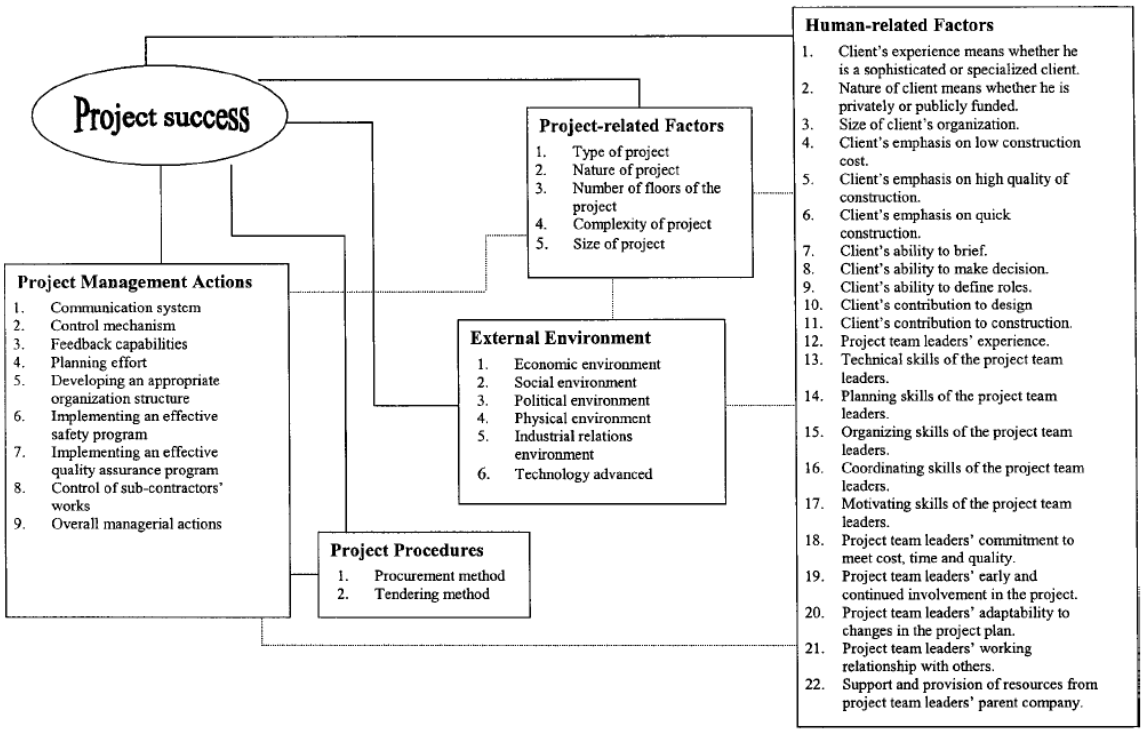


Figure 2-1. Framework for factors affecting project success (Chan et al. 2004)

These factors could be the most influential if the factors affecting a project were considered at the macro viewpoint. The chances to be an important factor for a project would be lower than other factors. Chan et al. (2004) asserted that "project success is a function of project-related factors, project procedures, project management actions, human-related factors and external environment and they are interrelated and intrarelated." They also pointed out the potential relationships between factors and groups.

Framework of Success Criteria for Design/Build Project

Framework of success criteria for design/build projects (Chan et al. 2002) mainly addressed the concept of a project success and what to measure to achieve project success in design/build projects. The authors mention that measuring project success is a complex task since success is intangible and can hardly be agreed upon. The general concept of project success remains ambiguously defined because of varying perceptions. Each project participant will have his or her own view of success. It depicts that owners, contractors, and architects have a different perspective of project success. According to the authors, project success is the goal, and the objectives of budget, schedule, and quality are the three normally accepted criteria to achieve the goal. Each project has a set of goals to accomplish, and they serve as a standard to measure performance. The authors addressed that the criteria for a construction project in general can be classified under two main categories, one being hard, objectives, tangible, and measurable, and the other soft, subjective, intangible, and less measurable. The integration of success and criteria is shown in Figure 2-2.

As shown in Figure 2-2, some of examples are provided, for hard, objectives, tangible, and measurable such as time, cost, quality, profitability, technical performance, completion, functionality, health and safety, productivity, and environmental sustainability and for soft,

Figure 2-2. Criteria for project success (Chan et al. 2002)

subjective, intangible, and less measurable, such as satisfaction, absence of conflicts, professional aspects. The unique idea proposed by this article is to add time concepts, like phases of construction, to success criteria. With respect to the time parameter, measures of success are different for each phase of the construction process (see Figure 2-3).

Phase	Pre-Construction (Past)	Construction (Current)	Post-Construction (Future)
Objective Measure	1. Time 2. Cost	1. Time 2. Cost 3. Health & Safety	1. Profitability
Subjective Measure	1. Quality 2. Technical Performance 3. Satisfaction of Key Project Participants	1. Quality 2. Technical Performance 3. Productivity 4. Satisfaction of Key Project Participants - Conflict Management	1. Satisfaction of Key Project Participants, End-Users and Outsiders - Completion - Functionality - Aesthetics - Professional Image - Educational, Social & Professional Aspects 2. Environmental Sustainability

Time Horizon →

Figure 2-3. Framework for project success of design/build projects (Chan et al. 2002)

As far as objective measures are concerned (see Figure 2-3), a maximum of three items are in the construction phase (current) and only one item is in post-construction phase (future). For the subjective measures, two major items with five sub-items are at the post-construction phase (future) and three items are at pre-construction phase (past). The numbers of items in the subjective measure are greater than the objective measure. It depicts that there are more intangible criteria available in design/build projects in terms of successful projects.

Project Performance Measure

Balanced Scorecard

The balanced scorecard method (Kaplan and Norton 1992) tracks the key elements of a company's strategy – from continuous improvement and partnerships to teamwork and global

scale. The balanced scorecard consists of four important perspectives: customer, financial, innovation and learning perspective, and internal business perspective. It is based on a set of measures that gives top managers a fast but comprehensive view of the business. The balanced scorecard provides answers to four basic questions (Kaplan and Norton 1992);

- How do customers see us? (customer perspective)
- What must we excel at? (internal perspective)
- Can we continue to improve and create value? (innovation and learning perspective)
- How do we look to shareholders? (financial perspective)

As shown in Figure 2-4 the balanced scorecard links among four perspectives and how results are achieved. According to the authors, one of the benefits of using the balanced scorecard is to show managers the most critical factors on their project. There are several companies that have used the balanced scorecard and they have shown that it meets their managerial needs (Kaplan and Norton 1992). The balanced scorecard has two major levels. The first level brings together, in a single

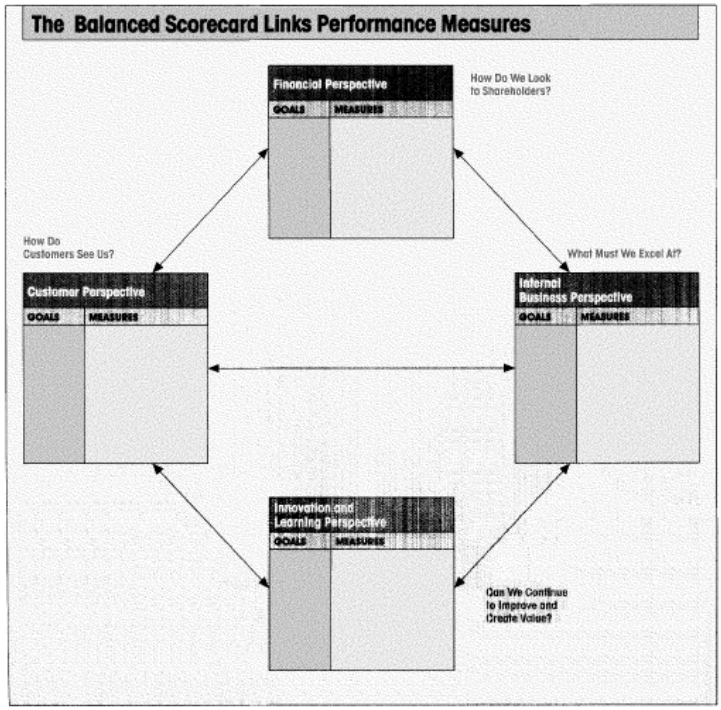


Figure 2-4. Balanced scorecards (Kaplan and Norton 1992)

management report, many of the seemingly disparate elements of a company's competitive agenda such as becoming customer oriented, shortening response time, improving quality, and emphasizing teamwork at the manager level. The second level guards against sub-optimization at senior management level, which means that it forces senior managers to consider all the important operational measures together. It makes it possible for senior managers to make sure that they use a balanced approach and to make sure improvement in one area has not been achieved at the expense of another, hence, the name balanced scorecard.

The balanced scorecard is based on management strategies and their measures. It aids managers in tracking their performances based on their strategies or goals and shows the relationship between four different perspectives and the impacts on the results. These concepts could be adopted to develop an application for this research. Project problems have different impacts on project success parameters and each success parameters could have different priority weights. The four perspectives of the balanced scorecard are equivalent to project success parameters. The authors did not mention how to set up the strategies because strategies can be different for different organizations or companies based on their needs or demand. But it shows how companies or organizations have improved their performances and the degree of improvement using the balanced scorecard.

Project Definition Rating Index

The project definition rating index (PDRI) was developed by Gibson and Dumont (1995) for the pre-project planning phase. It is an easy-to-use tool from the owners' perspective and this helps owners and design contractors interact during pre-project planning phase. The first PDRI is designed for the industry or heavy industry with 70 elements in 15 categories and has three different sections as bases for project decision, front-end definition, and execution approach. Figure 2-5 shows the list of 3 sections, 15 categories, and 70 elements incorporated in the PDRI.

I. BASIS OF PROJECT DECISION

A. Manufacturing Objectives Criteria
- A1. Reliability Philosophy
- A2. Maintenance Philosophy
- A3. Operating Philosophy

B. Business Objectives
- B1. Products
- B2. Market Strategy
- B3. Project Strategy
- B4. Affordability / Feasibility
- B5. Capacities
- B6. Future Expansion Considerations
- B7. Expected Project Life Cycle
- B8. Social Issues

C. Basic Data Research & Development
- C1. Technology
- C2. Processes

D. Project Scope
- D1. Project Objectives Statement
- D2. Project Design Criteria
- D3. Site Chars. Available vs. Required
- D4. Dismantling & Demolition Req'mts
- D5. Lead / Discipline Scope of Work
- D6. Project Schedule

E. Value Engineering
- E1. Process Simplification
- E2. Design & Material Alternatives Considered / Rejected
- E3. Design For Constructability Analysis

II. FRONT END DEFINITION

F. Site Information
- F1. Site Location
- F2. Surveys & Soil Tests
- F3. Environmental Assessment
- F4. Permit Requirements
- F5. Utility Sources with Supply Conds.
- F6. Fire Prot. & Safety Considerations

G. Process / Mechanical
- G1. Process Flow Sheets
- G2. Heat & Material Balances
- G3. Piping & Instrmt. Diags. (P&ID's)
- G4. Process Safety Mgmt. (PSM)
- G5. Utility Flow Diagrams
- G6. Specifications
- G7. Piping System Requirements
- G8. Plot Plan
- G9. Mechanical Equipment List
- G10. Line List
- G11. Tie-in List
- G12. Piping Specialty Items List
- G13. Instrument Index

H. Equipment Scope
- H1. Equipment Status
- H2. Equipment Location Drawing
- H3. Equipment Utility Requirements

I. Civil, Structural, & Architectural
- I1. Civil / Structural Requirements
- I2. Architectural Requirements

J. Infrastructure
- J1. Water Treatment Requirements
- J2. Loading / Unloading / Storage Facilities Requirements
- J3. Transportation Requirements

K. Instrument & Electrical
- K1. Control Philosophy
- K2. Logic Diagrams
- K3. Electrical Area Classifications
- K4. Substation Requirements / Power Sources Identified
- K5. Electric Single Line Diagrams
- K6. Instrument & Electrical Specs.

III. EXECUTION APPROACH

L. Procurement Strategy
- L1. Identify Long Lead / Critical Equipment & Materials
- L2. Procurement Procedures & Plans
- L3. Procurement Resp. Matrix

M. Deliverables
- M1. CADD / Model Requirements
- M2. Deliverables Defined
- M3. Distribution Matrix

N. Project Control
- N1. Project Control Requirements
- N2. Project Accounting Req'mts
- N3. Risk Analysis

P. Project Execution Plan
- P1. Owner Approval Requirements
- P2. Engr. / Constr. Plan & Approach
- P3. Shut Down/Turn-Around Req'mts
- P4. Pre-Commissioning Turnover Sequence Requirements
- P5. Startup Requirements
- P6. Training Requirements

Figure 2-5. PDRI sections, categories, and elements (Gibson and Dumont 1995)

The PDRI is based on the scope definition, i.e. the degree of scope definition at the pre-project planning phase. If the scope is well defined at that time, the impact on the project will be positive later. The degree of scope definition consists of five levels (Level 1 through 5) and definition of each level is as follows (Gibson and Dumont 1995):

1: Completion Definition
2: Minor Deficiencies
3: Some Deficiencies
4: Major Deficiencies
5: Incomplete or Poor Definitions

In the PDRI development stages, industry participants were asked to weigh elements by level of scope definitions and there was no limit on weighing. The weighting value represents each element's impact on total installed cost (TIC) stated as a percentage of the overall estimate. Therefore the lower the value, the better project scope definition is. Finally all the data are normalized by a 1,000 scale as the maximum score for the tool development. It represents the sum of all values (70 elements) in level 5 of the scope definition and is equal to 1,000. The scores of Levels 1 through 4 are rescaled proportionally compared to Level 5.

Figure 2-6 shows an example of the final version of PDRI. There is a difference in the level of scope definitions compared to the initial version. An option of "Not Applicable" is added into the level of scope definition. As mentioned earlier, the sum of Level 5 will be 1,000. In the example, category L, Procurement Strategy is assigned a maximum score of 16 which is the sum at Level 5 of items, L1, L2, and L3.

The maximum score of each item in Section L is 8, 5, and 3 for L1, L2, and L3 respectively. The score range of levels for an item L3 lies in between 0 for Level 1 and 5 for Level 5. If any user defines the level of scope definition of 70 items, then fill the column of

score with each assigned score by level of scope definition. The sum of column Score will show the levels of scope definition. The sum of Score will not exceed 1,000.

SECTION III - EXECUTION APPROACH							
CATEGORY Element	Definition Level						Score
	0	1	2	3	4	5	
L. PROCUREMENT STRATEGY (Maximum Score = 16)							
L1. Identify Long Lead / Critical Equipment and Mat'ls	0	1	2	4	6	8	
L2. Procurement Procedures and Plans	0	0	1	2	4	5	
L3. Procurement Responsibility Matrix	0	0				3	
CATEGORY L TOTAL							
M. DELIVERABLES (Maximum Score = 9)							
M1. CADD / Model Requirements	0	0	1	1	2	4	
M2. Deliverables Defined	0	0	1	2	3	4	
M3. Distribution Matrix	0	0				1	
CATEGORY M TOTAL							

Definition Levels

0 = Not Applicable **2 = Minor Deficiencies** **4 = Major Deficiencies**
1 = Complete Definition **3 = Some Deficiencies** **5 = Incomplete or Poor Definition**

Figure 2-6. Example of final version of PDRI (Gibson and Dumont 1995)

The PDRI is a checklist of the project at the pre-project planning phase. It is useful for owner, design contractors to check impacts on TIC based on the current situation. Although the PDRI is a useful tool for owners and designers, due to its limitation to the pre-project planning phase, it cannot be adopted by contractors for project executions. There will be more than one standpoint for the project checklist during project execution other than TIC. The drawback of this measurement tool is that the participant could manipulate the measurement. The participant knows which items have the most and least impacts on the result so it is possible for them to manipulate the results.

Leading Indicators

A leading indicators (LI) project (Choi et al. 2006) was initiated by the Construction Industry Institute (CII) to develop a new tool that can forecast the potential risk of not meeting specific project outcomes based on assessing potential problems (leading indicators). The definition of 'Leading Indicator' is that "leading indicators are fundamental project

characteristics and/or events that reflect or predict project health. Revealed in a timely manner, these indicators allow for proactive management to influence project outcomes" (Choi et al. 2006). Forty-three leading indicators were finally developed through three surveys and five different project success parameters were identified. The five different success parameters were cost, schedule, quality, safety, and owners' satisfaction. Each LI was evaluated in terms of each successful outcome using a five-point scale. If an LI has the highest negative impact on any success outcome, then five points will be assigned to it. If an LI has no negative impact on any success outcome, then zero will be assigned. And the rest will be in between. Weights of problems are based on aggregated scores. Based on this framework, a LI forecasting tool has been developed. In the tool usage, each problem is assessed as follows (Choi et al. 2006):

1: Serious (100%)
2: Major (75%)
3: Moderate (50%)
4: Minor (25%)
5: None (0%)
Not Applicable

The impact of each problem is assumed to be normally distributed. The total score of the tool will be 1,000. Unlike the PDRI, the higher score means positive or better and the lower score depicts negative or worse in forecasting project outcomes. This tool provides the score after assessing potential problems in terms of five different project success parameters plus one overall. Figure 2-7 shows an example output for this tool. The overall score represents the combination of each success parameter. The weight of each parameter is equal. The user is able to forecast the project outcome in terms of different success parameters. This tool aids the participants in understanding the degree of success in project outcome during the course of the project.

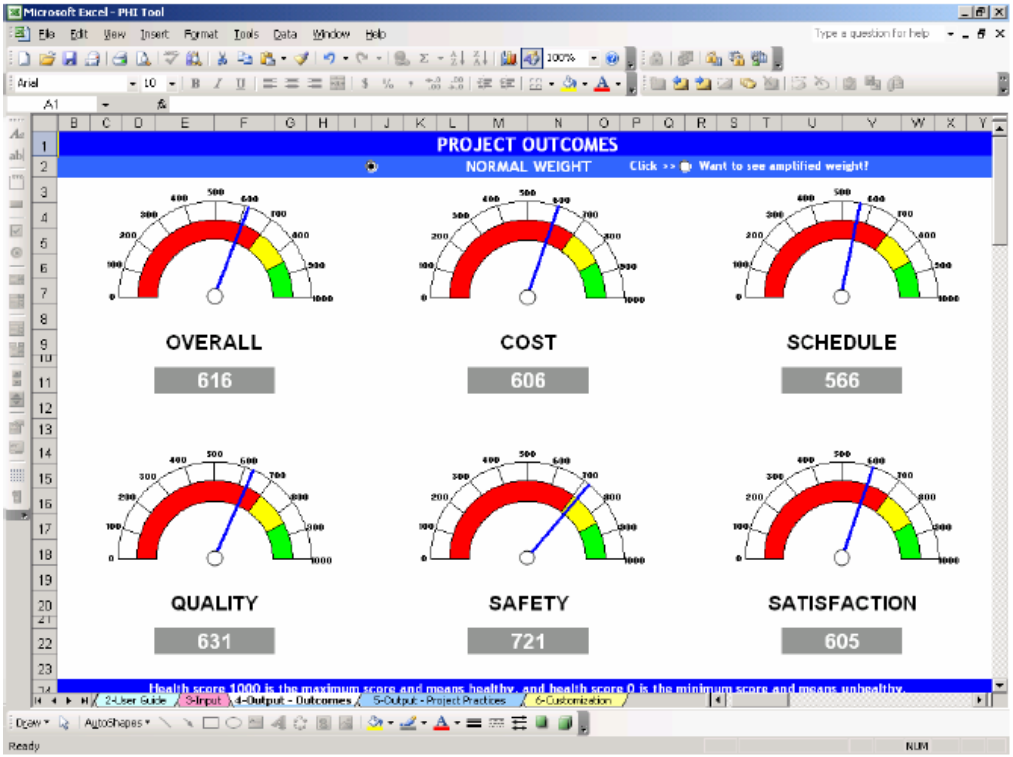


Figure 2-7. Example output of LI tool (Choi et al. 2006)

It is the first tool that considers more than one or two success parameters in the tool development. The tool provides the different success parameters but it fails to provide a guideline on where to fix or what to improve when the expected outcome is not as good as expected or vice versa. During the tool validation process, it was hard for the research team to get information on safety incident rates, quality, and satisfaction. Such information is not readily shared by companies. Information on cost and schedule was available to validate the tool but information on safety, quality, and satisfaction was not available. This methodology does not provide a clear predicted outcome when the weight of each success parameter is not equal.

Weight Computations in Index Models

Background

The domain of this research originally comes from index modeling. It is becoming popular among construction industry participants to measure performance or to meet needs. A

construction company will develop an index model to meet their owners' expectations and increase their performances. The company will follow a general procedure in developing the index model. An example of an index model for prediction of project success by project problems is shown in Table 2-1.

Table 2-1. General procedure of an index model

Step	Activities	Description
1	Develop Problems	- Select problems for measurements in the model
	↓	
2	Evaluate Problems on Success	- Survey Required - Evaluate Impacts/Weights of Problems on Success (Ex. From No Impact: 1 to High Impact: 6)
	↓	
3	Finalize Impacts or Weights	- Sum of Survey - Use average - Expertise's Opinion
	↓	
4	Decide Degree of Impact or Weights	- Expertise - Just Normal Distribution From 0% to 100%
	↓	
5	Application	- Tool Development (Mapping, Scorecards, Decision Trees, etc.)
	↓	
6	Tool Validation	- Required a Survey for Validation - Limitations & Recommendation

This is the general process for the development of an index model. One of the common examples of an index model is the PDRI developed by Dumont and Gibson (1995). It is specifically designed for the pre-project planning phase. It is an easy-to-use tool for the owners' perspective and this helps owners and design contractors interact during pre-project planning phase. The PDRI is based on the scope definition, exactly the degree of scope definition at the pre-project planning phase. If the scope is well defined at that time, the impact on the project will be positive later. The degree of scope definition consists of five levels. A lower level is

better than a higher level for the project scope definition. All elements are weighted by level of scope definitions and there is no limit on weighing. Weighing point represents that each element's impact on TIC stated as a percentage of the overall estimate. Therefore the lower points, the better project scope definition is. Finally all the data are normalized by 1,000 scale for the tool development. Table 2-2 shows an example of the PDRI. These are the weights of some items on the PDRI before they are normalized by 1,000 scale.

Table 2-2. Example of project definition rating index

SECTION II – FRONT END DEFINITION					
CATEGORY Element	1	2	3	4	5
J. INFRASTRUCTURE					
J1. Water Treatment Requirements	0%	5%	10%	15%	20%
J2. Loading/Unloading/Storage Facilities Requirements	1%	4%	8%	12%	14%
J3. Transportation Requirements	0%				10%

1 = Complete Definition *2 = Minor Deficiencies* *3 = Some Deficiencies*
4 = Major Deficiencies *5 = Incomplete or Poor Definition*
Source: Gibson and Dumont 1995

If an item J1 "Water Treatment Requirements" has some deficiencies, which is equivalent 3 in Table 2-2 on scope definitions, the estimator will add 10% of TIC for the contingency. The maximum weight is incomplete or poor definition and it will vary from item to item. In case of J1, the maximum allocated weight is 20% and the minimum is 0%. The final 20% is the average value of participants. Fifty four specialized team members from 31 companies who are very experienced in the construction industry decide all the weights on the PDRI. According to the PDRI report (Gibson and Dumont 1995), the total number of years of experience is 1,047 (709 years of project management and 338 years of estimating). The selection of reasonable weights is very important for the PDRI model, which is classified, in general, as an index model.

The basis for the PDRI model is Hackney's (1992) definition rating checklist. After weighing items on the list were completed, the PDRI results were compared to Hackney's

revised definition rating checklist. The results were similar. Hackney arbitrarily assigned maximum weights to each of the items in his checklist (Gibson and Dumont 1995). The weights shown in Table 2-3 pertain to industrial process plant projects. The magnitude of the weights reflects an estimate of the percentage cost overrun that might be expected in the overall project if information for an item was completely unknown. In general, the weights represent the relative ability of an item to affect the degree of uncertainty in the project estimate. The intent of the checklist was for each item to be scored prior to estimating the cost of the project.

Table 2-3. Hackney's (1992) revised definition rating checklist

Items	Max. Weight	Items	Max. Weight
General Project Basis		*Site Information (Continued)*	
Products and By-Products	100	Yard Improvements Available	40
Process Background	200	Review with Operations	25
Raw Materials	100	Review with Construction	25
Utilities & Services	50	*Engineering Design Status*	
Ownership Factor (multiplier)	-	Layouts	35
Process Design Status		Line Diagrams	50
Flow Balances	70	Auxiliary Equipment, Type and Size	70
Major Equipment, Type and Size	80	Buildings, Type and Size	35
Materials of Construction	50	Yard Improvement, Type and Size	55
Review of Process Design	70	Hazard Control Specifications	30
Site Information		Coating Specifications	20
Surveys	85	Review of Engineering Design	100
Climatological Information	25	*Detailed Design*	
Ordinances & Regulations	146	Drawings and Bills of Materials	45
Reusable Equipment	25	Drawing Reviews	35
Reusable Supports, Piping & Electrical	25	*Field Performance Status*	50
Buildings Available	30		
Utilities Available	25		

Source: Hackney 1992

The leading indicators project (Choi et al. 2006) was initiated by CII to develop a new tool that can forecast the potential risk of not meeting specific project outcomes based on assessing potential problems (leading indicators). 43 leading indicators were developed and five different project success parameters were identified. The five different success parameters are cost, schedule, quality, safety, and owners' satisfaction. The final product of project is a tool to forecast the project success based on assessment of current problems in a project. There were 84

survey participants. Each problem was evaluated in terms of their negative impact on each project success parameter. The range of scores shown in Table 2-4 is from 0 (no impact) to 5 (very high negative impact) in each potential problem.

Table 2-4. A six-point scale used for the questionnaire

Scale	No	Very Low	Low	Moderate	High	Very High
Point	0	1	2	3	4	5

Source: Choi et al. 2006

The computation of weights for project is the sum of all participants' score (aggregated scores) in each problem. There were issues on this computation with standard deviation of each sum of problem. To minimize the impacts of standard deviation, each sum was divided by its standard deviation for the initial (normal) weight. During the tool testing stage, the normal weight may not be sufficient enough to differentiate between outcome scores. So the weights were recomputed using third, fifth, seventh, and ninth power as shown in Table 2-5.

Table 2-5. Generating five different weighted scores for cost parameter

LI No.	Total Score	Normal Weight (W1)		Third Power Weight (W3)		Fifth Power Weight (W5)		Seventh Power Weight (W7)		Ninth Power Weight (W9)	
		SD	Weighted Score	SD^3	Weighted Score	SD^5	Weighted Score	SD^7	Weighted Score	SD^9	Weighted Score
1	369	0.62	594	0.24	1,539	0.09	3,987	0.04	10,329	0.01	26,762
2	313	0.83	379	0.56	554	0.39	811	0.26	1,188	0.18	1,739
3	343	0.85	402	0.62	552	0.45	759	0.33	1,042	0.24	1,432
4	317	0.81	390	0.54	592	0.35	899	0.23	1,364	0.15	2,070
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.

Source: Choi et al. 2006

Based on these five different weights, the tool validation was processed. After all, the potential users have options for the usage of these five different weights.

Concerns with Weights in Index Modeling

Three different index models have been addressed. The most important part of index modeling is the weighing process. Each model has its own way to compute the weights. A summary of the features of each model is shown in Table 2-6.

Table 2-6. Summary of three index models on weights

Model	Participants	Method	Weights on	Weighing Method
Hackney (1992)	-	Personal Experience	% of Cost Overrun	Arbitrary Personal Experience
PDRI (1995)	54 Industry Expertise	Workshops	Contingency on TIC	Use Average
Leading Indicator (2006)	84 Industry Participants	General Surveys	Impact on 5 Different Successes	Aggregated Score/Standard Deviation

Hackney's (1992) model is based on personal experience and weighs on percentage of cost overrun. Fifty four industry experts spent a lot of time on establishing weights for TIC in the PDRI. The first index model is based on personal experience and know-how and the second one has support from 54 specialized industry expertises in the same field for this specific research. For the first one, it is 100% based on experts' opinion. It is rationally possible to use the average value as weights for the PDRI because the participants had enough experiences in the same field and kept communicating on this subject during the workshop. For the leading indicator project, there were 84 industry participants. It is a general research survey such as is done of most cases of this type of research. In this case, it is not recommended to use the average because participants may have different field of specialties and there may be a gap between their total amount of experience. The aggregated score is the best solution for this project. But as mentioned above, it had problems with standard deviation during weighing process and tool tune-up process. The final solution was to use normal, third, fifth, seven, and ninth power as shown in Table 2-5. There are two questions regarding this solution. One is "What is the real generalized weight (impacts on success)?" and the other is "Which one is more important, tool or weights?" The answer for the first one is a part of this research. The possible answer for the second question may be weights. Based on weights, any kind of tool can be developed. That tool could be similar to the leading indicator, balanced scorecards, mapping, or decision tree

tools. The answer to the second question may be controversial. But the importance of weight in the index model is extremely high.

What Hackney (1992) and the PDRI model measure is tangible costs and schedule durations. That is why both used percentage as weights. Problems and items on the checklist were developed for these two measures. There is a demand for new project success parameters. Cost and schedule are the most traditional common project success parameters. But there are some more parameters that impact the success of projects, e.g. safety, quality, and owner's satisfaction. The first two models are designed mainly for cost and schedule but the leading indicator project is designed for five different success parameters. The five success parameters are cost, schedule, quality, safety, and satisfaction. Two of these parameters could be tangible like cost and schedule but the rest of parameters cannot be tangible. The leading indicator project has to be consistent in measuring the impacts of each success parameter. A project should not have more than one method to measure something. For example, the contingency (%) for cost and schedule and degrees of impact for quality, safety, and satisfaction may not be a good solution for weight. In the opinion of this author, one of the main reasons to use different powers in the leading indicator project is the range of evaluation is too narrow so that aggregated scores did not make any big difference at the end. But if a wider range of impacts had been used, the aggregated scores could have made a bigger difference and then the standard deviation could have been larger as well. The range of impacts or measurements is optimal between five and nine (Spector 1992). So the evaluation method of a problem's impact on each success parameter shown in Table 2-4 is reasonable. Users could not tell the degree of differences over this range in the survey. The first two models, Hackney's and the PDRI could be considered as special cases and the last model, the leading indicator, could be considered as a general case from

surveys to tool validation process. From this perspective, there are some concerns with weight and their method of computation no matter what the specialized area is in the index modeling.

Simple Multi-Attribute Rating Technique Using Swing (SMART*S*)

The final deliverable from this research is an easy-to-use tool for the contractors when they have to make decisions on what to deal with among their potential or current problems under any circumstance of multi project success parameters with different priorities. The first step to using the tool could be a selection of the most critical problems based on the priority weights of project success parameters. The second step of the process is additionally applied to the degrees of severity of problems. In the second step it is assumed that the degree of severity is normally distributed. Considering the first step, the methodology of simple multi-attribute rating technique using swing (SMART*S*) (Edwards and Barron 1994) would be applied. SMART*S* is based on an elicitation procedure for weights. SMART*S* uses linear approximations to single utility functions, an additive aggregation model, and swing weights. It is assumed that a decision maker has a project called Project A and has two potential job sites, Sites 1 and 2, and that their main selection criteria for a job site are cost and schedule. Under this circumstance, the procedure of SMART*S* will be as follows:

Step 1: Purpose and Decision Makers

The selection of best job site for Project A with options of Site 1 and 2

Step 2: Develop a List of Attributes (Criteria)

Cost and schedule of Project A

Step 3: Objects of Evaluations

Evaluation of two job sites in terms of cost and schedule.

Suppose, Site 1 is better than Site 2 in cost, the weights are 90 for Site 1 and 70 for Site 2. On the other hand, Site 2 is better than Site 1 for the schedule, the weights are 60 for Site 1 and 95

for Site 2. The numbers represent the degree of preferences (value dimension) of each job site in cost and schedule. The higher value, the higher the preference is. Based on this evaluation, the following matrix is obtained:

	Cost	Schedule
Site 1	90	60
Site 2	70	95

Step 4: Determine Swing Weights

Edwards and Barron (1994) use the term "swing" to refer to the operation of changing the score of some object of evaluation on some dimension from one value to a different value. Suppose that the schedule is more important than the cost. If the range of weights is in between 0 and 100, the weight of schedule would be 100. Then how much important is cost, compared to schedule, 100? One thing is sure that the weight of cost cannot be 100. Because cost is less important than schedule and the weight of schedule is 100. It is just assumed that the decision maker thinks the weight of cost is 80, compared to schedule, 100.

Step 5: Calculate Swing Weights

In Step 4, the weight of each attribute is decided as 100 for schedule and 80 for cost. Using these weights, swing weights will be computed as follows:

	Weights	Swing Weights	
Cost	80	80/180 =	0.45
Schedule	100	100/180 =	0.55
Total	180		1.00

Step 6: Calculate All Multi-Attribute Utilities

Using the matrix from Step 3 and swing weights, all multi-attribute utilities (aggregated score) are computed. The computations for Sites 1 and 2 are as follows:

$$\text{Site 1: } 90 \times 0.45 + 60 \times 0.55 = 73.50$$

$$\text{Site 2: } 70 \times 0.45 + 95 \times 0.55 = 83.75$$

Step 7: Make a Decision

Based on the computation in Step 6, the decision maker has to come up with a final decision. The utility values of this example depict the preference. It means that the higher value is more favorable than the lower value and therefore, the higher aggregated score from Step 2 would be the first best option. The aggregated score for Sites 1 and 2 are 73.50 and 83.75 for respectively. Under the given conditions for the selection criteria, evaluation of sites in terms of criteria, and weights of criteria, Site 2 would be a better choice than Site 1.

The general procedure of SMART*S* has been addressed so far. Regarding options, there are two more considerations in this method. One is the dominance option and the other is independence of options (Edward 1977, Edwards and Barron 1994, Oyetunji 2001). Although there are some ways to check the dominance, it could be possibly done by visual checking. In addition to the dominance, all options have to be independent of each other. It means that they have to have low correlations between them. The options that have the same correlations would be combined to one option or one of these options would be eliminated. These two issues will be addressed in more detail in Chapter 5.

Edwards and Barron (1994) addressed two key ideas underlying SMART*S*. One is the multi-attribute utility and the other is the strategy of heroic approximation. In terms of the multi-attribute utility, if anything is valued at all, it is valued for more than one reason. Any outcome of a decision is most naturally described by a vector of numbers that relate to value. Edwards and Barron (1994) developed SMART*S* based on two principles. One is that simpler tools are easier to use and so more likely to be useful. The second is that the key to appropriate selection

of methods is concern about the trade-off between modeling error and elicitation error. In its previous version, SMART, included the judgments of the indifference between pairs of hypothetical options which seemed difficult and unstable. The authors believed that more nearly direct assessments of the desired quantities were easier and less likely to produce elicitation errors and call that view the strategy of heroic approximation. Users of that strategy do not identify formally justifiable judgments and then figure out how to elicit them. Rather they identify the simplest possible judgments that have any hope of meeting the underlying requirements of multi-attribute utility measurement, and try to determine whether they will lead to substantially suboptimal choices in the problem at hand. If not, they try to avoid elicitation errors by using those methods.

In this chapter, the literature review for this research has been presented in terms of its relevance to the research. The first part of this chapter addresses the major factors and/or problems of projects. The major issue is to define factors and/or problems without their impacts on projects. Another part focuses on the current trends or research of how to measure project performances and its usage as a tool or index model in terms of project success parameters. This section clearly shows the current research needs in this area for some more work on multi-project success parameters and their relationships with problems. In other words, the current research focuses on a single or two success parameters. The last part of this section addresses some considerations on weight computation and a methodology for the application.

CHAPTER 3
STRATEGY AND DESIGN

Overview

This chapter will mainly address the overall strategy and design of this research. This includes the data collection, the methodologies for this research such as canonical correlations and factor analysis (exploratory factor analysis and confirmatory factor analysis). Regarding data collection, the background for the data collection will be discussed. Canonical correlations will address concepts and how it relates to this research and their outputs. The concepts of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) will also be addressed.

Development of Problems

All the necessary data were obtained from the leading indicators project (Choi et al. 2006). It developed 43 potential problems with five project outcomes (success parameters). The 43 problems are listed in Appendix A. The defined five success parameters by the research team were 1) Cost; 2) Schedule; 3) Quality/Operability (Quality); 4) Safety; and 5) Stakeholder satisfaction. These five parameters are generally and traditionally used to measure project success in many industries. The definitions for each parameter are as follows (Choi et al. 2006):

- **Cost**: Cost performance is viewed in terms of overall actual final cost versus the established project budget. Secondary cost outcomes can include cost/cash flow deviation (compliance with spending plans), cost efficiency (how efficiently an asset is design and constructed verses similar facilities in industry), and consumption of contingency or reserves.

- **Schedule**: Schedule performance is viewed in terms of overall actual final duration versus the planned project duration. Secondary schedule performance can include outage duration performances and overall engineering and construction cycle time (for certain fast rack projects).

- **Quality/Operability**: Quality and Operability are outcomes that are based upon a facility being capable of operating per its intended function and that the quality of the facility and construction craftsmanship matches the intended asset lift. (For example, if we build a facility that is intended to make 100 widgets a day, the facility should be capable of making 100 widgets a day).

- **Safety**: Safety as an outcome is a combination of construction safety during the course of the project and the overall safety considerations of the new facility that will enable it to operate safely over its production life-cycle. Construction safety involves the accidents to personnel within the construction zone and is generally viewed in terms of recordable or Days Away or Restricted Time (DART) cases. Facility safety is focused on a more long-term outcome and is based upon the facility having the equipment, protections, and or warning/safety devices, safe job procedures, energy control procedures etc. required for the facility to operate in a safe manner.

- **Stakeholder Satisfaction**: Stakeholder satisfaction is the overall pride, satisfaction, contentment and/or happiness that the stakeholders have with the outcome of the project. It is somewhat a measure of the potential for future repeat business.

After the 43 potential problems were finalized, eight different groups were formed based on the characteristics of these potential problems. The definition of each problem group (Choi et al. 2006) is listed in Appendix B. Due to grouping, each problem is renamed based on its characteristics (group). For example, L1, which is *the project team is lacking in the necessary expertise, experience, breadth and depth to successfully executed the project*, now is renamed as AL1. The label indicates that it belongs to Alignment (AL) group and its assigned the number is 1. The rest of problems will be renamed based on their characteristics. The renamed problems by group and with assigned numbers are shown in Appendix A. Based on these 43 problems, this research will be addressed. Table 3-1 shows the number of groups of problems and their number of problems.

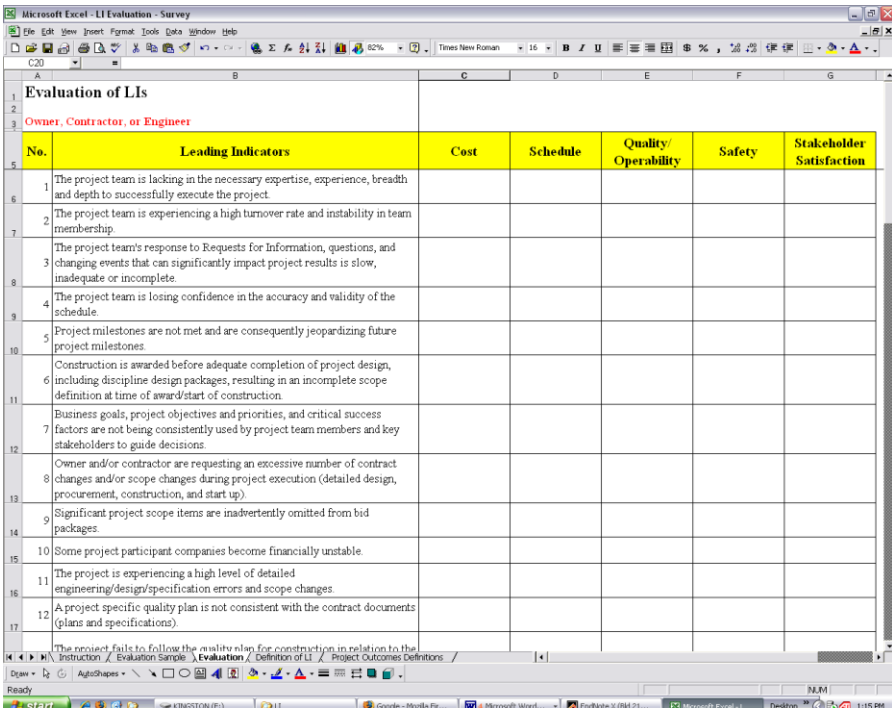
Table 3-1. Groups of potential problems

Groups		Number of Problems
Alignments	(AL)	8
Constructability	(CA)	4
Change Management	(CM)	4
Contracting	(CO)	3
Quality Management	(QM)	5
Safety Practice	(SP)	7
Project Control	(PC)	8
Team Building	(TB)	4
Total		43

Alignment (AL) and Project Control (PC) have the most number of problems and Contracting (CO) has the least number of problems. Safety Practice (SP) has seven problems, which is the second highest number of problems among groups.

Data Collection

As mentioned in the previous section, the initial data set come from leading indicator project (Choi et al. 2006). The survey file consisted of five worksheets. The five worksheets were Introduction, Evaluation Sample, Evaluation, Definition of LI, and Project Outcomes Definition. Figure 3-1 shows a screen capture of the Evaluation worksheet of the survey. There is an explanation of the general concept of the survey about how to evaluate LIs as well as contact information for the author in the Introduction worksheet. The Evaluation Sample worksheet shows how to evaluate LIs in the sheet. The Evaluation worksheet is the main data collection form for survey participants. Two definition worksheets show the definition of LI and project outcomes to help the survey participants understand the concepts.



Evaluation of LIs

Owner, Contractor, or Engineer

No.	Leading Indicators	Cost	Schedule	Quality/ Operability	Safety	Stakeholder Satisfaction
1	The project team is lacking in the necessary expertise, experience, breadth and depth to successfully execute the project.					
2	The project team is experiencing a high turnover rate and instability in team membership.					
3	The project team's response to Requests for Information, questions, and changing events that can significantly impact project results is slow, inadequate or incomplete.					
4	The project team is losing confidence in the accuracy and validity of the schedule.					
5	Project milestones are not met and are consequently jeopardizing future project milestones.					
6	Construction is awarded before adequate completion of project design, including discipline design packages, resulting in an incomplete scope definition at time of award/start of construction.					
7	Business goals, project objectives and priorities, and critical success factors are not being consistently used by project team members and key stakeholders to guide decisions.					
8	Owner and/or contractor are requesting an excessive number of contract changes and/or scope changes during project execution (detailed design, procurement, construction, and start up).					
9	Significant project scope items are inadvertently omitted from bid packages.					
10	Some project participant companies become financially unstable.					
11	The project is experiencing a high level of detailed engineering/design/specification errors and scope changes.					
12	A project specific quality plan is not consistent with the contract documents (plans and specifications).					
	The project fails to follow the quality plan for construction in relation to the					

Figure 3-1. A screen capture of evaluation worksheet (Choi et al. 2006)

A total of 84 respondents completed the final survey: 26 were owners and 58 were contractor/engineer/designer respondents. These respondents represented 32 companies: 14 owners companies and 18 contractor/engineer/designer companies (Choi et al. 2006). Participants were asked to evaluate each problem using a six point scale with the following response options: no, very low, low, moderate, high, and very high negative impact on five success parameters. If any LI has no impact on any success parameter, it will be marked as 0 and vice versa. Table 3-2 shows a six point scale used for questionnaire.

Table 3-2. A six point scale

Scale	No	Very Low	Low	Moderate	High	Very High
Point	0	1	2	3	4	5

Source: Choi et al. 2006

In addition to the original 84 data sets, another 16 data sets were collected during the summer 2008 timeframe via email and phone interviews. This data collection used the same survey form as the leading indicator project (Choi et al. 2006) as shown in Figure 3-1. The respondents represent 9 companies of contractors. The final number of survey responses for this research is 100, which came from 14 owners companies and 27 contractor/engineer/designer companies.

Data Transformation

The range of evaluation for the impact on any success parameter is based on a six point scale. The minimum value is 0 with no negative impact on any success parameter and the maximum value is 5 with the highest negative impact on any success parameter. The main methodology of leading indicator study (Choi et al. 2006) is the aggregation of the scores for each problem evaluated by each participant. The sum of the scores is the basis of the measurement tool. In this case the range of between 0 and 5 works well. The proposed analysis methodology for this research is confirmatory factor analysis. In the data set for this statistics,

the numbers 0 and 1 usually represent opposite values based on the characteristics of data set against each other such as ‘on’ and ‘off’ or ‘male’ and ‘female’ respectively. In the current data set, there are some data points with values of 0. This may lead to a misunderstanding in terms of data interpretation. Therefore, it is necessary to revise the current scale. If any problem has no negative impact on any success parameter, it will be marked as 1 and if any problem has the highest negative impact on any success parameter, it will be marked as 6. To change the scale of evaluation, the current evaluation of each problem is incremented by 1. For example if a problem has an evaluation value of 1, it will be changed into 2. This research uses this rescaled data set. Table 3-3 shows the comparison on a six point scale.

Table 3-3. Comparisons of current and rescaled

Scale	No	Very Low	Low	Moderate	High	Very High
Current	0	1	2	3	4	5
Rescaled	1	2	3	4	5	6

Data Analysis

Descriptive Statistics

In this section, all the survey data will be analyzed in terms of each problem within each success parameter, using descriptive statistics. It is assumed that each problem has a different negative impact on each success parameter. Table 3-4 shows some of problems with their descriptive statistics. A full set of descriptive statistics for all 43 problems is available in Appendix C. The highest mean value is SP1 in Safety with 5.85 and the lowest mean value is CA4 in Safety with 2.56. The range of standard deviations is between 0.56 and 1.486 for PC2 in Schedule and for AL2 in Safety respectively. Each problem has different mean values for its success parameters. It shows that the negative impacts of problems on success parameters varies. For example CA4 has a mean value of 5.62, which is pretty high in Cost but has a mean value of 2.56, which is much lower than that of Cost in Safety.

Table 3-4. Examples of problems with descriptive statistics

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
	Cost	542	5.42	0.619	11.43
	Schedule	540	5.40	0.600	11.11
AL1	Quality	507	5.07	0.803	15.84
	Safety	471	4.71	1.211	25.71
	Satisfaction	522	5.22	0.844	16.16
	Cost	481	4.81	0.880	18.29
	Schedule	475	4.75	0.187	18.68
AL2	Quality	451	4.51	1.063	23.57
	Safety	353	3.53	0.421	42.10
	Satisfaction	491	4.91	1.150	23.42
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.		
	Cost	481	4.81	1.036	21.54
	Schedule	504	5.04	0.958	19.01
TB4	Quality	415	4.15	1.236	29.78
	Safety	387	3.87	1.309	33.82
	Satisfaction	507	5.07	0.951	18.76

Notes: 1. S.D=Standard Deviation, 2 C.V=Coefficient of Variation (%)

Regarding safety as a success parameter, there may be some disagreement between problems and its impacts. The value of standard deviation in Safety appears generally higher than the others. It is hard to have a clear overview of standard deviations because the standard deviation is based on the mean values. Forty three problems have different mean values so it is impossible to compare standard deviation on an apple to apple basis. To have a clearer view of standard deviations, the coefficient of variation is used. It is the ratio of standard deviation to the mean. Sometimes it is represented as ratio (digits) or percentage. The equation for coefficient of variation is shown in Equation 3-1 (Weisstein 2009b).

$$\text{Coefficient of Variation} = \frac{\text{Standard Deviation}}{\text{Mean}} \times 100\ (\%) \qquad \text{(Equation 3-1)}$$

The values of the coefficient of variation are different from those for standard deviation because it considers the mean values. The highest coefficient of variation is CM4 in Safety with a value of 43.14 and the lowest coefficient of variation is SP1 in Safety with a value of 9.78.

In the previous paragraph, the statistics data were provided in terms of each problem for any success parameters. At this point, one question rises. How about the values of the descriptive statistics in terms of success parameter? It would be helpful for understanding the data in depth. This information showed what the survey participants unintentionally thought in terms of their priorities of project success parameters even though they were not directly asked to set the priority of each success parameter. If any success parameter has a higher mean value than others, it means that the success parameter has a higher priority (impact) than the others. Based on data collected from 100 surveys, the computed mean values of success parameters are shown in Table 3-5.

Table 3-5. Mean values of success parameters

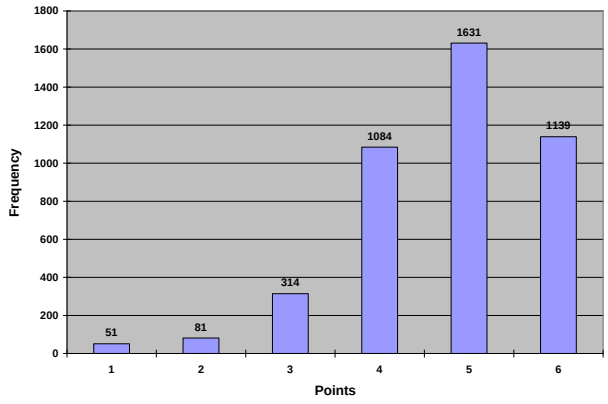
Success Parameter	Cost	Schedule	Quality	Safety	Owner's Satisfaction
Mean	4.76	4.82	4.13	3.73	4.68

The mean value of Schedule is the highest at 4.82 and the mean value of Safety is the lowest at 3.73. Cost and Schedule have the two highest mean values among project success parameters. The survey participants evaluate problems considering Cost and Schedule the most among the five success parameters.

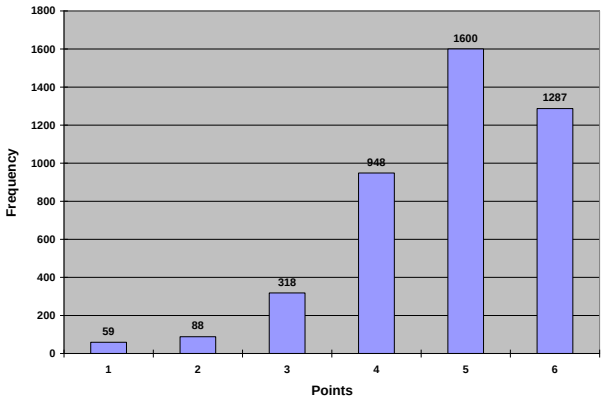
Data Tendency Analysis

As mentioned earlier, each problem has different responses to each success parameter in terms of mean values. It is evident that each problem has different priorities that affect success parameters. The tendency of data is defined as the number of frequencies of each point during

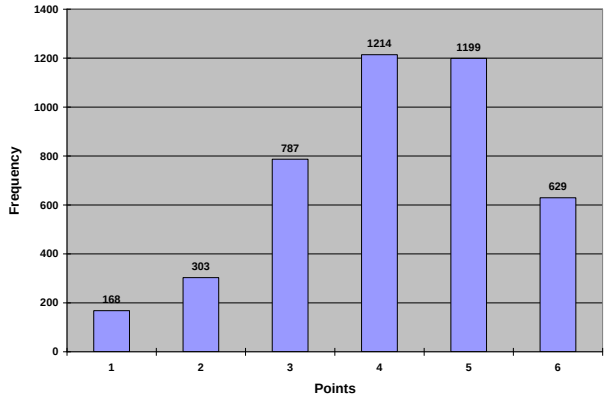
the evaluation process of each problem in terms of each success parameters. Figure 3-2 shows the frequency histogram of each success parameter.



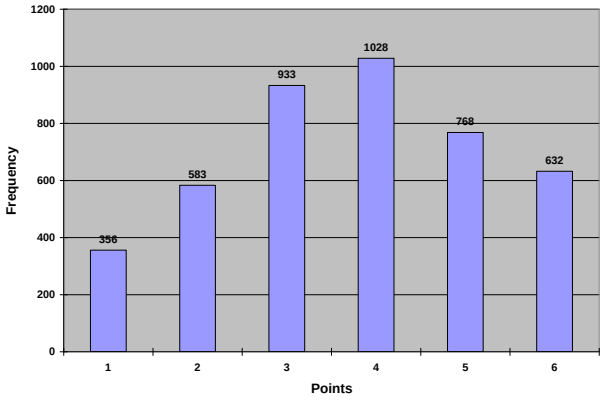
A) Cost



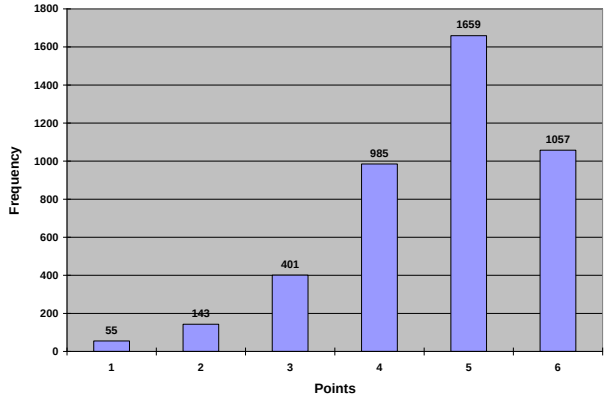
B) Schedule



C) Quality



D) Safety



E) Satisfaction

Figure 3-2. Frequency histogram

Regarding data tendency, cost, schedule, and satisfaction have the similar tendency as shown in Figures 3-2 A, B, and E. Quality and safety show similar tendency as shown in Figures 3-2 C and D. The frequency histograms of cost, schedule, and satisfaction are skewed to the left and the frequency histograms of quality and safety look like they are normally distributed. It shows that the cost, schedule, and satisfaction groups have more problems with a value of 5 or greater than those of the group of quality and safety. The two most frequent values are 5 and 6 for Cost, Schedule, and Satisfaction and 4 and 5 for Quality and Safety.

From the descriptive statistics and frequency histograms, we can conclude that there are two main characteristics of data. One is that each problem has a different response to any success parameters and the other is that each success parameter has a different priority. There are no problems that always have the highest score or lowest score to all five success parameters. It is apparent that problems' responses to success parameter are dynamic. In addition to this, the frequency of values over 5 in Cost, Schedule, and Satisfaction are higher than those for Quality and Safety.

Methodology

Background

The data available for this research are for 43 potential problems with 8 groups of parameters. The input data mainly are provided by industrial project companies so it may not be suitable for other types of construction projects such as commercial, residential, and heavy civil. It is important to understand the relationships within each success parameter before identifying a relationship between problems and success parameter. To define the relationships between variables (problems), there are several statistical methods (techniques) available to define the relationships between variables such as 1) correlations, 2) multiple regression, 3) factor analysis, and 4) canonical correlations. Regarding the methodology for the analysis of relationships

between problem groups and success parameters, SMART*S* will not be mentioned in this chapter because it was already addressed in Chapter 2.

Correlations show the strength and direction of a linear relationship between two variables. It could be ideal for this data analysis. But there are 43 variables for this research and it means the generated matrix will be a matrix of 43×43. Since 43 variables are grouped by their characteristics, it would be better comparing group to group not a variable to variable. Correlation does not allow for group-to-group analysis, hence it is not recommended for this data analysis. Multiple regression consists of one set of dependent (criterion) variables and more than two sets of independent (predictor) variables. It will provide one linear combination of dependent and independent variables. One of the main purposes of multiple regressions is to develop a prediction model. For the purposes of this study multiple regression is not required. Factor analysis is commonly used to determine the number of "factors" being measured by a variable. The main function of this method is to determine the underlying factor(s) and data reduction. There are two types of methods in this analysis. They are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Regarding confirmatory factor analysis, it will be addressed later in this study. The data has been grouped as eight different groups. It is not necessary to perform factor analysis to determine factors for this research but is necessary to check how many factors would be extracted before performing CFA. Canonical correlations show the relationships between two variable sets. Each set has more than two variables. Unlike multiple regressions, canonical correlations generate two linear combinations, one for criterion and the other for predictor. This is the main difference between multiple regression and canonical correlations. Canonical correlation provides the maximum correlations between two sets. It is suitable for this research to define relationships between groups of multiple variables.

Canonical Correlation

Overview

Canonical correlation analysis is used to explore relationships between two variable sets when each variable set has at least two variables (Thompson 1984). One variable set represents independent variables and the other variable set represents dependent variables. "The canonical correlation is optimized such that the linear correlation between two latent variables is maximized. Whereas multiple regressions is used for many-to-one relationships, canonical correlation is used for many-to-many relationships (Garson 2008a). " Due to many-to-many relationships, it is possible to have more than one correlation relating two sets of variables. A total number of possible correlations are set by a number of smaller variable sets. For example, if there are two variable sets available which are a set of three variables and another set of five variables, then the number of possible correlations between these two sets is three. With respect to the characteristics of computation of correlations, the first extracted correlation usually has the highest value and the last correlation has the lowest value. To test the significance of canonical correlation, Wilk's lambda is commonly used. Some of key concepts and terms are as follows (Garson 2008a):

- "Canonical variate: A canonical variate is a linear combination of a set of original variables in which the within-set correlation has been controlled. There are two canonical variates per canonical correlation. One is the dependent canonical variable, while the one for the independent variables may be called the covariate canonical variable."

- "Canonical correlation: A canonical correlation, also called a characteristic root, is a form of correlation relating two sets of variables. As with factor analysis, there may be more than one significant dimension (more than one canonical correlation), each representing an orthogonally separate pattern of relationships between the two latent variables."

- "Eigenvalues: The Eigenvalues are approximately equal to the canonical correlations squared. They reflect the proportion of variance in the canonical variate explained by the canonical correlation relating two sets of variables. This is only useful when there is more than one extracted canonical correlation and more than one Eigenvalue, one for each canonical correlation."

- "Significance Tests (Wilks's lambda): Wilks's lambda is used in conjunction with Bartlett's V to test the significance of the first canonical correlation. If $r < 0.05$, the two sets of variables are significantly associated by canonical correlation. Degree of freedom equal $P \times Q$, where P = number of variables in variable set 1 and Q = number of variables in variable set 2. This test establishes the significance of the first canonical correlation but not necessarily the second."

Computation of canonical correlations

To compute canonical correlations, the data will be computed as a correlation matrix and the program uses this as an input data as shown in Figure 3-3 where there are two subsets of variables *x* and *y*.

$\boldsymbol{R_{xx}}$	$\boldsymbol{R_{xy}}$
$\boldsymbol{R_{yx}}$	$\boldsymbol{R_{yy}}$

Figure 3-3. Input matrix (Ainsworth 2008)

The correlation matrix of *x* is denoted as R_{xx} and the correlation matrix of *y* is denoted as R_{yy}. R_{xy} and R_{yx} are the cross-correlation matrices of the two subsets. To find canonical correlations, Equation 3-2 (Ainsworth 2008; Dunteman 1984) is applied:

$$\lambda = R_{xx}^{-1}R_{xy}R_{yy}^{-1}R_{xy}^{T} = R_{yy}^{-1}R_{xy}^{T}R_{xx}^{-1}R_{xy} \qquad \text{(Equation 3-2)}$$

To solve this equation, the determinant of $R_{xx}^{-1}R_{xy}R_{yy}^{-1}R_{xy}^{T} - \lambda I$ has to vanish since the columns of this matrix has to be linearly dependent to meet the conditions of the characteristic equation (Dunteman 1984). *I* is the identification matrix. From the values of λ, the canonical variates will be computed by each extracted λ for the subset of *x* and *y*.

Results of canonical correlations

The correlations are the strength and direction of a linear relationship between two variables. The degree of linear correlation varies in the range of –1 and +1. If $\rho = 0.6$, the relationship is considered as a moderate relationship and if $\rho = 0.9$,the relationship is considered a strong relationship (Olson 1987). The results will be categorized as follows:

- No Relationship : $\rho < 0.6$
- Low Moderate : $0.6 \leq \rho < 0.7$
- Medium Moderate : $0.7 \leq \rho < 0.8$
- High Moderate : $0.8 \leq \rho < 0.9$

If the absolute values of correlation are less than 0.6, then it will be considered that there is no relationship. The ranges of the results in this study lie between 0.541 as a minimum and 0.898 as a maximum. Most of correlations fall into the category of moderate. There is no negative or opposite direction of values in correlation. The detailed results are shown in Tables 3-6 through 3-10.

Table 3-6. Canonical correlations of cost parameter

	AL	CA	CM	CO	PC	QM	SP	TB
AL	1.000							
CA	0.781	1.000						
CM	0.690	0.648	1.000					
CO	0.658	0.541	0.694	1.000				
PC	0.819	0.861	0.729	0.666	1.000			
QM	0.816	0.722	0.673	0.594	0.782	1.000		
SP	0.772	0.755	0.584	0.556	0.781	0.794	1.000	
TB	0.757	0.687	0.619	0.573	0.736	0.585	0.724	1.000

Table 3-7. Canonical correlations of schedule parameter

	AL	CA	CM	CO	PC	QM	SP	TB
AL	1.000							
CA	0.712	1.000						
CM	0.836	0.631	1.000					
CO	0.632	0.580	0.612	1.000				
PC	0.777	0.688	0.756	0.657	1.000			
QM	0.768	0.674	0.773	0.669	0.778	1.000		
SP	0.753	0.705	0.666	0.646	0.637	0.746	1.000	
TB	0.784	0.713	0.743	0.647	0.705	0.739	0.727	1.000

Table 3-8. Canonical correlations of quality parameter

	AL	CA	CM	CO	PC	QM	SP	TB
AL	1.000							
CA	0.674	1.000						
CM	0.789	0.670	1.000					
CO	0.691	0.670	0.639	1.000				
PC	0.785	0.808	0.773	0.712	1.000			

Table 3-8. Continued

	AL	CA	CM	CO	PC	QM	SP	TB
QM	0.660	0.639	0.658	0.591	0.628	1.000		
SP	0.748	0.718	0.675	0.601	0.855	0.637	1.000	
TB	0.789	0.661	0.737	0.679	0.783	0.605	0.786	1.000

Table 3-9. Canonical correlations of safety parameter

	AL	CA	CM	CO	PC	QM	SP	TB
AL	1.000							
CA	0.812	1.000						
CM	0.779	0.774	1.000					
CO	0.831	0.831	0.761	1.000				
PC	0.832	0.898	0.883	0.867	1.000			
QM	0.797	0.850	0.868	0.811	0.889	1.000		
SP	0.694	0.626	0.556	0.595	0.596	0.562	1.000	
TB	0.847	0.809	0.771	0.759	0.807	0.719	0.580	1.000

Table 3-10. Canonical correlations of satisfaction parameter

	AL	CA	CM	CO	PC	QM	SP	TB
AL	1.000							
CA	0.803	1.000						
CM	0.836	0.817	1.000					
CO	0.811	0.762	0.815	1.000				
PC	0.842	0.866	0.883	0.822	1.000			
QM	0.834	0.735	0.831	0.800	0.862	1.000		
SP	0.774	0.762	0.785	0.710	0.836	0.778	1.000	
TB	0.874	0.732	0.721	0.718	0.781	0.733	0.664	1.000

As shown in Table 3-6 through 3-10 above, each problem group has different correlations between problem groups within success parameters. This trend already addressed in the section 3.5 in this chapter. The highest and lowest correlations in Cost are the combination of PC and CA with a correlation value of 0.861 and the combination of CO and CA with a correlation value of 0.541. In Schedule, there is no significantly high moderate correlation except for the correlation of CM and AL with a correlation value of 0.836, which is the highest correlation in Schedule. The lowest correlation is produced between CO and CA with a correlation of 0.580. There are two high moderate correlations in Quality. They are the combinations of PC and CA and SP and PC with correlations of 0.808 and 0.855 respectively. On the other hand, the lowest

correlation is 0.591 of the combination of QM and CO. The highest correlation in Safety is 0.898, which is the combination of PC and CA. The lowest correlation in Safety is 0.556 from the combination of SP and CM. There are more correlations of less than or equal to 0.6 in Safety, especially the most of combinations with SP, compared to other success parameters. The highest correlation is the combination of PC and CM with a correlation of 0.883 and the lowest correlation is 0.664 by the combination of TB and SP in Satisfaction. There is no correlation less than or equal to 0.6 in this parameter. In Safety and Satisfaction parameters, the most of problem groups show medium and high moderate correlations. The number of high moderate correlations is larger than that of Cost, Schedule, and Quality parameter. It clearly shows that a few combinations of problem groups have high correlations in Cost, Schedule, and Quality parameters. In other words, some problem groups have some tendencies for high correlations in those success parameters. But most of combinations in Safety and Satisfaction parameters usually have high correlations. It depicts that most of problems in these parameters have tendencies for high correlations, compared to another three parameters.

Factor Analysis (Exploratory vs. Confirmatory)

One of the main purposes of this research is to define the relationships between problem groups and success parameters. To achieve this goal, the proper methodology has to be chosen, considering the data available. The data available are the negative impacts of problems on each success parameter. To satisfy the data set and purpose of this research, confirmatory factor analysis (CFA) has been chosen. Before CFA is addressed, the general concepts of factor analysis will be discussed.

Factor analysis is commonly used in education, sociology, and psychology because it is sometimes impossible to measure directly the variables effects in these disciplines. Factor analysis is a statistical procedure for uncovering factors by observed variables. The main

purpose of this method is to reproduce the relationships among observed variables by factors (Brown 2006). Then what are factors? The factors are sometimes called 'Latent Variables.' The factors are something that cannot be directly observed or measured such as depression but can be measured indirectly by their effects on observed variables. It is evident why it is common in education, sociology, and psychology. There are two types of factor analysis. One is exploratory factor analysis (EFA) and the other is confirmatory factor analysis (CFA). Both of them share the basic concepts of factor analysis but its application is different. EFA is a data-driven approach and there is no specification such as number of factors and relationships between factors and variables (Brown 2006). Therefore, the main purpose of EFA is to reduce the number of data into small number of data set by factors. Sometimes it is used for the early stage of CFA to check the number of factors and validation. One of the best examples of EFA is the intelligence quotient (IQ) test. Some of problems in IQ can be categorized by factors or latent variables when it is calculated. Unlike EFA, CFA is a theory-driven approach based on such parameters as the number of factors and the pattern of indicators and factor loadings, etc (Brown 2006). The researcher has to decide, at least expect the number of factors and other related matters, or has a theory to test before he/she can perform CFA (Brown 2006; Thompson 2004). In factor analysis, the relationships between latent variables and indicator variables are shown as arrows. For example there is a latent variable, A, and an indicator variable, B. The relationship between two variables would be represented by an arrow as shown in Figure 3-4.

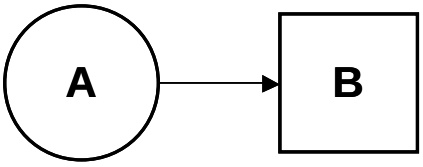


Figure 3-4. A relationship between two variables

A relationship depicted by an arrow in factor analysis is considered as a causal relationship (Brown 2006). In Figure 3-4, the relationship between A and B is a causal relationship. It means that the latent variable, A, causes the indicator variable, B. In another words, the variable, A, could be explained by the variable, B. "The main concern of CFA is to evaluate how well a CFA model (S) reproduces the sample covariance matrix (S) of the measured variables" (Brown 2006). The researcher has to find the best-fitted model explained by the sample covariance matrix. In this section, the overall concepts of factor analysis have been discussed. Although the main methodology of this research is CFA, it is necessary to address the concept of EFA in detail because both of them share the same methodology and terminologies.

Exploratory Factor Analysis (EFA)

Overview

The overall concepts of factor analysis in EFA and CFA have been discussed above. Before CFA is discussed in detail, it is helpful to discuss EFA first to understand CFA. All the terminologies and components are common to both EFA and CFA. In this section, the main concepts and purposes of EFA will be shown with some examples.

The concepts of factor or latent variables have already been addressed previously. The main purposes of factor analysis can be summarized as shown below (Thompson 2004):

1) Evaluation of score validation
2) Development of theory regarding nature of construct
3) Summary of relationships using factor

These three purposes do not always fall into the category of EFA. The last two are commonly used for EFA. The most common purpose of EFA would possibly be 'Summary of relationships using factor'. In another words, it is possible to explore the potential relationships or look for a pattern, trend, or characteristics using EFA in a set of data. Based on this exploration, the researcher could develop and test a theory using CFA. During an EFA process,

it is possible to define the relationships and characteristics of a data set and it is finally also possible to reduce the number of data sets. Table 3-11 shows an example of EFA data. This is a hypothetical data set for the evaluation of the author done by seven students. Each student evaluated the author using values ranging from most agree with a value of 9 and the least agree with a value of 1.

Table 3-11. Heuristic EFA data

Student	Measured Variable					
	Handsome	Beautiful	Ugly	Brilliant	Smart	Dumb
Barbara	6.00	5.00	4.00	8.00	6.00	2.00
Debora	8.00	7.00	2.00	7.00	5.00	3.00
Jan	9.00	8.00	1.00	9.00	7.00	1.00
Kelly	5.00	4.00	5.00	9.00	7.00	1.00
Murray	4.00	3.00	6.00	9.00	7.00	1.00
Susan	7.00	6.00	3.00	7.00	5.00	3.00
Wendy	3.00	2.00	7.00	7.00	5.00	3.00
Mean	6.00	5.00	4.00	8.00	6.00	2.00
S.D.[1]	2.16	2.16	2.16	1.00	1.00	1.00

Notes: 1. Standard Deviation.
Source: Thompson 2004.

The data in Table 3-11 have six measured variables and seven data points. These six measured variables are indicator variables in factor analysis. One of the purposes of factor analysis is to explore the relationships and then to summarize the relationships into a smaller number of latent constructs (Thompson 2004). There are several statistical methods available to summarize the relationships including correlations. Table 3-12 shows the bivariate correlation matrix for Table 3-11.

Table 3-12. Bivariate correlation matrix

Variables	Measured Variable					
	Handsome	Beautiful	Ugly	Brilliant	Smart	Dumb
Handsome	1.00	1.00	(1.00)	0.00	0.00	0.00
Beautiful	1.00	1.00	(1.00)	0.00	0.00	0.00
Ugly	(1.00)	(1.00)	1.00	0.00	0.00	0.00
Brilliant	0.00	0.00	0.00	1.00	1.00	(1.00)
Smart	0.00	0.00	0.00	1.00	1.00	(1.00)
Dumb	0.00	0.00	0.00	(1.00)	(1.00)	1.00

Source: Thompson 2004.

All the values in Table 3-12 are bivariate correlations between measured variables. The correlations in the parenthesis depict negative correlation. From this matrix, the relationships among measured variables are easily defined. There are two possible latent factors found here. One latent factor is related to handsome, beautiful, and ugly and the other latent factor is related to brilliant, smart, and dumb. The first factor could be labeled as 'Physical Attractiveness' and the second factor could be labeled as 'Intellectual Prowess' (Thompson 2004). There is no significant relationship between these latent factors. The raw data initially have six measured variables as shown in Table 3-11 and 3-12. Now this data set could be summarized by two latent factors instead of six variables. This is a reduction of number of variables based on latent factors. This is commonly used in EFA to reduce the number of variables. The second finding from this example is to show the relationships between measured variables within each latent factor. It is evident that there is no significant relationship between latent factors in the above example. In addition to this, the correlations in Table 3-12 show the relationships between measured variables. Regarding the variables related to Physical Attractiveness, 'Handsome' and 'Beautiful' have the same direction, which is being positive and 'Ugly' has the opposite direction compared to 'Handsome' and 'Beautiful'. Similar interpretations can be found in the variables of Intellectual Prowess. These findings can be summarized as shown in Figure 3-5.

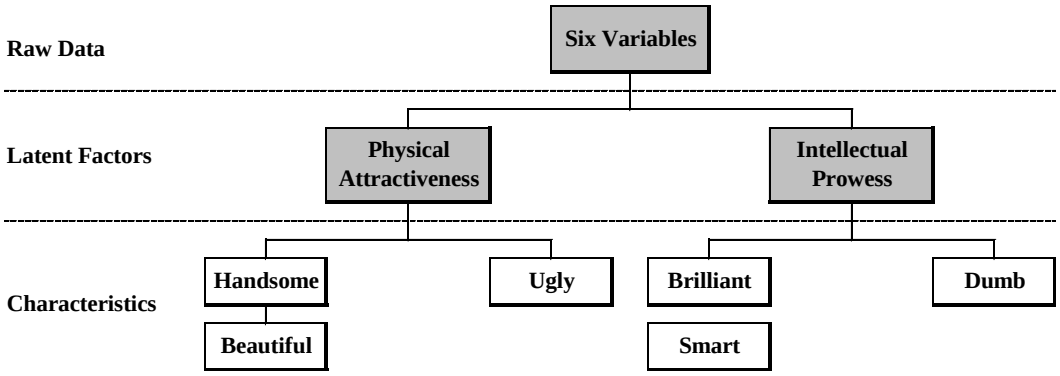


Figure 3-5. Summary of latent factors and variables

From the original six measured variables, two latent factors are found and the characteristics of variables are defined within each latent factor. This example has only six variables and seven participants. It is very clear and easy to categorize variables by their meaning or wording such as handsome, beautiful, ugly, brilliant, smart, or dumb. In actual research projects, there will be more variables with more survey participants. It is impossible to figure out latent factors and characteristics of variables from the variables directly by wordings. Through this example, the overall concept of EFA is addressed clearly.

Number of factors with extraction methods

In the previous section, the general concepts of EFA are addressed with an example. From the example, two factors are extracted from six variables. How many factors can be extracted from a set of data? The maximum possible number of extracted factors is equal to the number of variables. If there are six variables available as example above, the maximum extracted number of factors is six or less than six. If the number of extracted factors is equal to the number of variables, then it will not be necessary to perform factor analysis.

There are five methods available to extract factors. The five methods are 1) Statistical Significance Tests; 2) Eigenvalue Greater Than 1.0 Rule; 3) Scree Test; 4) Inspection of the Residual Correlation Matrix; and 5) Parallel Analysis (Thompson 2004). Each method has its pros and cons but the two most common methods are 'Eigenvalue Greater Than 1.0 Rule' and 'Scree Test'. The Eigenvalue method is the default function to extract factors in most statistical packages (Thompson 2004). The definition of Eigenvalue has already been addressed in the previous section. Recall the example with six variables with two latent factors. Table 3-13 shows Eigenvalues of the example.

Table 3-13. Eigenvalues for the example

Measured Variable	Factor	
	I	II
Handsome	1.00	0.00
Beautiful	1.00	0.00
Ugly	(1.00)	0.00
Brilliant	0.00	1.00
Smart	0.00	1.00
Dumb	0.00	(1.00)
Sum of Squared Column Values	3.0	3.00

Source: Thompson 2004

The sum of squared column values is an Eigenvalue of each extracted factor. Each value in Table 3-13 is a pattern/structure coefficient. The sum of the Eigenvalues is equal to the number of measured variables. Here in this example, 3.0 + 3.0 = 6.0. Each factor reproduces 50% (3.0/6.0 = 0.5) of information regarding the original data. So the sum of these two Eigenvalues is equal to 6 or 100%. Thompson (2004) made the following four statements about Eigenvalues in EFA:

1) The number of Eigenvalues is equal to the number of measured variables.

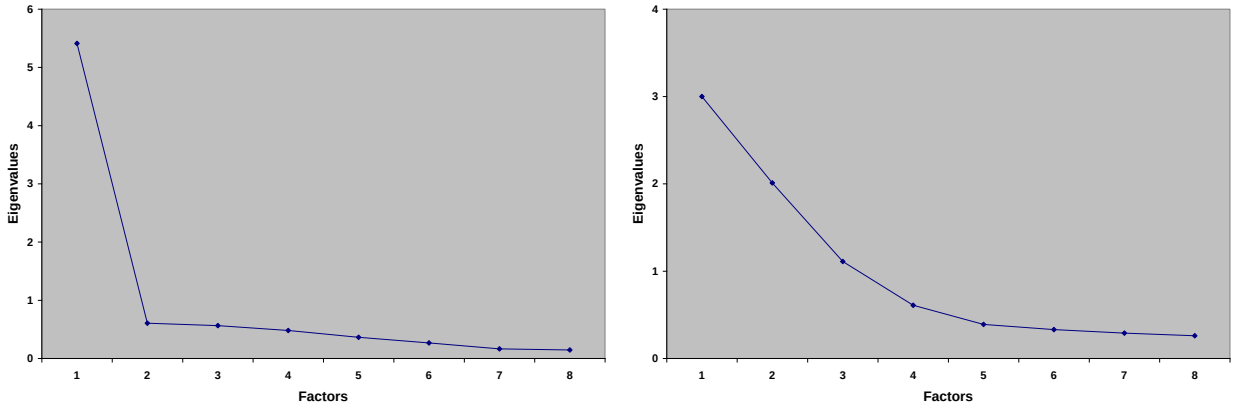
2) The sum of Eigenvalues is equal to the number of measured variables.

3) An Eigenvalue divided by the number of measured variables indicates the proportion of information.

4) The sum of the Eigenvalues for the extracted factors divided by the number of measured variables indicates the proportion of the information.

The fundamental concept of using the Eigenvalue greater than 1.0 rule is based on the logical thinking behind these four observations. The computation of an Eigenvalue is based on the sum of squared pattern/structure coefficients of measured variables within an extracted factor. There may be one or more than one variable available for an extracted factor. If there is only one variable available for that extracted factor with a coefficient value of 1.0 and the coefficient values of rest of variables are zero, then the Eigenvalue of that factor would be 1.0 (Thompson

2004). The other common method is 'Scree' test. The Eigenvalue method is based on the numerical value to extract factors, while the Scree test is based on a graphical test to determine the number of factors. The extracted factors will be plotted on the x-axis (horizontal) and their Eigenvalues on y-axis (vertical). A line can be drawn to connect the coordinates of each factor and its Eigenvalue. "Factor extraction should be stopped at the point where there is an "elbow," or leveling of the plot" (Brown 2006; Thompson 2004). The Scree test is basically looking for a spot where there is a sharp or big change in slope of the line on the graph drawn. "This visual approach, not invoking statistical significance, is sometimes called a "pencil test," because a pencil can be laid on the rightmost portion of the relevant graph to determine where the elbow or flattening seems to occur" (Thompson 2004). Besides the statistical significance, it is an easy process to extract factors using the Scree test when there is clearly a steep point that changes the slope in the line. Two examples are shown in Figures 3-6A and B.



A) Quality B) Made up example

Figure 3-6. Scree plot.

Figure 3-6A is associated with one of project success parameters, Quality, and Figure 3-6B is a made up example to compare the slope of lines in Scree plots. Both of them have the same number of measured variables and the sum of Eigenvalues is equal to eight. According to the Scree test method, only one factor could be extracted in Figure 3-6A because there is a big slope

change at 'Factor 2' in the plot. From that point, there are no big slope changes until the last potential factor, 'Factor 8'. On the other hand Figure 3-6B has no significant changes in slope. In this case, it would be impossible to extract factors using the Scree test method.

The Eigenvalue greater than 1.0 and the Scree test are two most common methods to extract factors. These two methods are available on most statistical computer packages such as the Statistical Analysis Software (SAS®) and the Statistical Package for the Social Sciences (SPSS®). EFA will be performed as the preliminary stage of CFA even though the main methodology of this research is CFA. The method to be used to extract factors would be the combined Eigenvalue method and Scree test.

Confirmatory Factor Analysis (CFA)

Overview

The overall concepts of factor analysis for EFA and CFA have been addressed and the background of EFA has been discussed in more detail so far. The reason why CFA has been chosen for this research has been explained as well. In this section, the parameters of factor analysis models and an example relating to CFA factor analysis will be discussed.

There are five terms in general factor analysis models. They are factor loadings (λ), factor variances (λ^2), unique variances (ε), exogenous (independent) variables, and endogenous (dependent) variables. The explanation of these are as follows (Brown 2006):

- Factor Loadings (λ): Normally factor loadings are regression slopes between latent variables and indicator variables. Sometimes they can be correlations when there is no cross loading between latent variables and indicator variables.

- Factor Variances (λ^2): Factor variances are variances explained by latent factors.

- Unique Variances ($\varepsilon = 1 - \lambda^2$): Unique variances are variances that are not explained by latent factors. This is the difference between factor analysis and multiple regressions. Factor analysis considers the measurement error.

- Exogenous (Independent) Variables: These are independent (latent) variables in the model. They are not caused by other variables and normally latent variables are exogenous variables in the model. An oval or circle represents exogenous variables in the factor analysis models. An arrow starts from exogenous variables.

- Endogenous (Dependent) Variables: These are dependent (indicator) variables caused by other variables in the model. The indicator variables are almost always endogenous variables. But sometimes, latent variables are also endogenous variables. It depends upon the model specifications but not for this research. A box or square represents endogenous variables in the factor analysis models. An arrow ends endogenous variables.

Regarding factor loadings, there are some issues on the interpretation of factor loadings. It may be a little bit different from each perspective (Thompson 2004). These represent the impact of latent variables on indicator variables on many excellence models (Bassioni et al. 2008; Eskildsen et al. 2001). So for this research, the interpretation of factor loading will be the same as excellence models. The values in Table 3-12 would be factor loadings on each latent factor that is 'Physical Attractiveness' and 'Intellectual Prowess'. In this example, a factor variance of each factor would be 1 and its variance would be 0. 'Physical Attractiveness' and 'Intellectual Prowess' are the exogenous variables and three measured variables for each exogenous variable are the endogenous variables. Figure 3-4 shows an example of exogenous and endogenous variables using an arrow to show the causal relationship. 'A' is an exogenous (independent) variable within an oval and 'B' is an endogenous (dependent) variable within a box. An example of the factor analysis model (Brown 2006) relating to CFA will be discussed from here to help understand CFA in depth.

This example is about 'Depression.' This model has one latent variable (depression) and four indicator (measured) variables; 1) D_1: Hopelessness; 2) D_2: Feelings of Worthlessness/Guilt; 3) D_3: Psychomotor Retardation; and 4) D_4: Sleep Disturbance. The depression cannot be measured directly so it can be measured only indirectly from its effects on each indicator. It means that the latent variable (depression) is manifested by these four indicator variables. This

is based on 300 samples. There are various methods to denote the factor analysis model but in this research, the denotations and results are chosen as shown in Figure 3-7.

A) Denotation of model. B) Results of model

Figure 3-7. Example model (Brown 2006).

In Figure 3-7A, a latent factor (depression) is denoted as η_1 within an oval and four indicator variables are denoted as Y_N, where $N = 4$. The factor loading of each indicator variable is denoted as λ_{N1}, where $N = 4$. Unique variances are denoted as ε_N, where $N = 4$. All the related equations and results in this model are shown in Table 3-14.

Table 3-14. Equations and results of the model

Equations	Numerical Results
$Y_1 = \lambda_{11}\eta_1 + \varepsilon_1$	$D_1 = 0.83\eta_1 + 0.31$
$Y_2 = \lambda_{21}\eta_1 + \varepsilon_2$	$D_2 = 0.84\eta_1 + 0.29$
$Y_3 = \lambda_{31}\eta_1 + \varepsilon_3$	$D_3 = 0.79\eta_1 + 0.37$
$Y_4 = \lambda_{41}\eta_1 + \varepsilon_4$	$D_4 = 0.75\eta_1 + 0.44$

Source: Brown 2006.

The results of the example model shown in Figure 3-7 indicate that the most impact on depressions among four indicators is D_2 (Feelings of Worthlessness/guilt) with $\lambda = 0.84$ and $\varepsilon = 0.29$. The least impact on the latent variable is D_4 (Sleep Disturbance) with $\lambda = 0.75$ and $\varepsilon = 0.44$. At this point the researcher may conclude that depression is manifested by four indicator variables and D_2 has the highest impact and D_4 has the least impact on the latent variable. To satisfy the results requirement of a CFA model, it is required to satisfy the goodness-fit-test

because one of the purposes of CFA is to test any theory and all the data has to be reproduced based on latent variables. The goodness-of-fit test is used to show the gap between the original data and the data reproduced by factors. It is an evaluation process of how well the factor model reproduces the original data. So it is necessary to check the goodness-of-fit test in CFA models. There are various methods and indices to perform the goodness-of-fit test and it will be discussed later on in this study.

CFA models for this research

The data set available for this research has 43 problems, categorized into eight different problem groups. The data has 100 observations. These problems are evaluated in terms of their negative impacts on five different success parameters. The range of impacts is from no impact (1) to highest impact (6). From this background, it is clear to infer that each success parameter represents a latent variable and eight problem groups represent indicator variables for each success parameter. There are five different CFA models for this research because this research addresses five different success parameters and eight different problems groups. The five latent variables are Cost, Schedule, Quality, Safety, and Satisfaction and the eight problems groups are Alignment (AL), Constructability (CA), Change Management (CM), Contracting (CO), Quality Management (QM), Project Control (PC), Safety Practices (SP), and Team Building (TB). The initial CFA model for each parameter is shown in Figure 3-8.

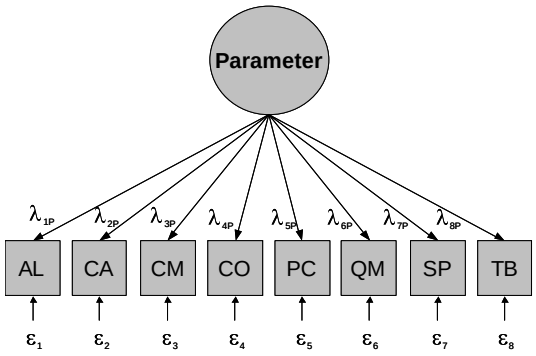


Figure 3-8. Initial CFA model for each success parameter

These five initial CFA models can be rewritten in an equation format similar to that shown in Table 3-14. These equations for each success parameter are shown in Table 3-15, where *P* = each success parameter (Cost, Schedule, Quality, Safety, and Satisfaction).

Table 3-15. Initial CFA model equations

Equations	
$AL = \lambda_{1p}\eta_p + \varepsilon_1$	$QM = \lambda_{5p}\eta_p + \varepsilon_5$
$CA = \lambda_{2p}\eta_p + \varepsilon_2$	$PC = \lambda_{6p}\eta_p + \varepsilon_6$
$CM = \lambda_{3p}\eta_p + \varepsilon_3$	$SP = \lambda_{7p}\eta_p + \varepsilon_7$
$CO = \lambda_{4p}\eta_p + \varepsilon_4$.	$TB = \lambda_{8p}\eta_p + \varepsilon_8$.

As shown in the descriptive statistics in Chapter 3, each problem reacts differently to each different success parameter. It may be questionable whether each success parameter gets affected by all eight problem groups but it is evident that eight problem groups do not have the same impact on five success parameters. The hypotheses to test, using these models are as follows:

- $H_{o:}$ Each latent factor (success parameter) is manifested by the eight problem groups.
- $H_{o:}$ Each problem group will have a different impact on each success parameter if the statement above would be true.

The main hypothesis is to test whether or not each latent factor (success parameter) would be manifested by the eight problem groups. This is for a number of problem groups needed for each success parameter, for example eight problem groups or less than that. And then a degree of impact on each success parameter of related problem groups would be determined.

Procedures for CFA Models

Overview

The generalized procedure for the CFA model is shown in Figure 3-9. There are three key steps in the procedure. One is Cronbach's alpha, another is the normality check, and the third one is the goodness-of-fit test. The articles reviewed (Bassioni et al. 2008; Cheng 2001;

Eskildsen et al. 2001; Garson 2008c; Ko et al. 2005) have performed these steps for their CFA models or CFA models for SEM. Cronbach's alpha is used to test the quality of the data set for CFA models in micro perspective and for factor analysis in macro perspective. The normality check is used to aid in selecting the CFA model method, such as Maximum Likelihood (ML) and Weighted Least Squares (WLS). The normality of data affects the CFA models in terms of estimating parameters. The parameter estimates can be underestimated or overestimated when a wrong method is chosen (Brown 2006). So they have to be chosen carefully. The Goodness-of-

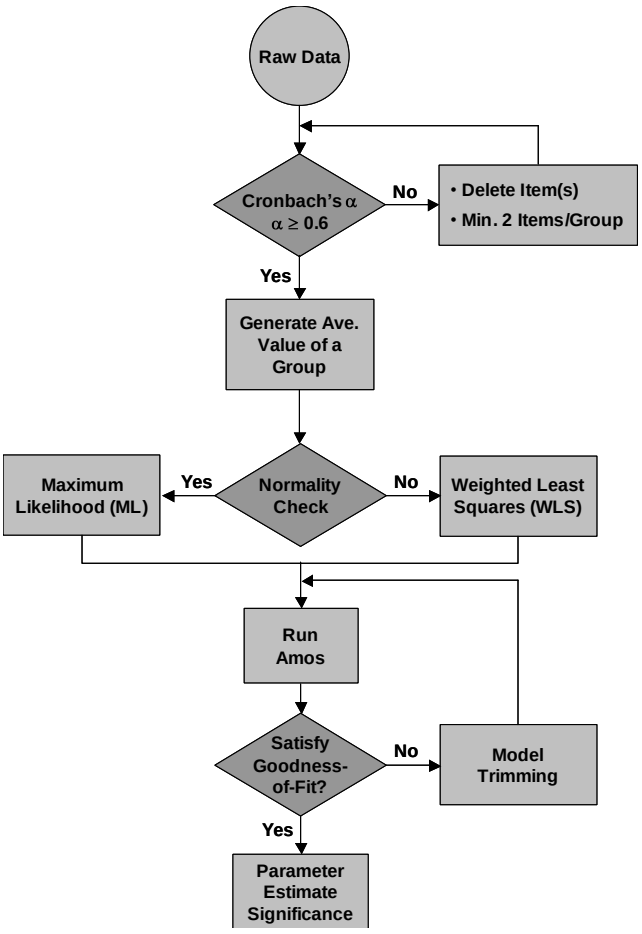


Figure 3-9. CFA model procedure

fit test is the last step of CFA models. This step shows how well a CFA model explains the raw data set in terms of latent factors. To satisfy this step, the null hypothesis should fail to reject in

the case of χ^2 for example a p value has to be greater than 0.05 at $\alpha = 0.05$. There are various methods for the goodness-of-fit tests and they will be discussed later.

There is a difference between all the articles reviewed and the procedure in Figure 3-9. Only one article addresses the improvement of CFA model goodness-of-fit test by deleting some of paths in the model (Garson 2008c). The rest of articles do not address the model trimming. The reasons why they do not explain this step may be:

- The CFA model satisfies the goodness-of-fit test.
- The CFA model does not satisfy the goodness-of-fit test but the goodness-of-fit test result falls into a certain excusable range from the researcher's perspective (There are no specific or official guidelines for this).
- One of the purposes of CFA models is to test a theory. If the null hypothesis gets rejected and/or the goodness-of-fit test does not meet, then the theory is not right regarding at least what it says. So it is not necessary to improve CFA models in this case because it is proven to be wrong.

If the goodness-of-test does not meet the required criteria, then there is a difference between a model and a set of data and it could mean that the theory to be tested is wrong. As mentioned earlier, if any CFA models do not meet the goodness-of-fit test, then the CFA models will be trimmed until the goodness-of-fit test is satisfied. All eight problem groups may not result in major impacts on each success parameter even though each problem group may have different impacts. The model trimming procedure will be necessary to find those problem groups that may not manifest in impacts on each success parameter. More detailed information on each step will be discussed in the following sections.

Crobach's (Coefficient) alpha

The first step is to check Cronbach's alpha (α), which is also called 'Coefficient Alpha' or 'Reliability Coefficient' (Garson 2008b). The Cronbach's alpha is a measure of the internal consistency of a scale and the higher the alpha value is the better (Garson 2008c; Spector 1992).

"Alpha measures the extent to which item responses obtained at the same time correlate highly with each other" (Garson 2008b). The alpha value represents a direct function of both the number of items and their magnitude of intercorrelation. The range of alpha is from 0 to 1 (Garson 2008c). The number of items and intercorrelation affect the alpha value. Cronbach's alpha normally has higher values when there is a higher number of items. The main use of Cronbach's alpha is to check that everything is measured that has to be measured in the same way. The checking process is sometimes referred to as checking "Construct" (Garson 2008b). It is assumed that there is an error if an item is less correlated with others (Spector 1992). For example, if everybody measures something in common, then the measurements will be highly correlated with each other. The computation of alpha value is shown in Equation 3-3 (Spector 1992).

$$\alpha = \frac{k}{k-1} \times \frac{\sigma_T^2 - \Sigma\sigma_I^2}{\sigma_T^2} \qquad \text{(Equation 3-3)}$$

Where,

k : Number of items

σ_T^2 : Total variance of the sum of the items

σ_I^2 : Total variance of an individual item

To use the raw data for CFA models, the coefficient alpha values have to be checked. The acceptable range of coefficient alpha values varies by authors, with requiring a value greater than 0.6 (Bassioni et al. 2008; Hair et al. 1998) or 0.7 (Garson 2008b; Garson 2008c) even though all agree that the higher the value is the better. For this research, the minimum acceptable Cronbach's alpha value is greater than 0.6. If some Cronbach's alpha value is less than 0.6, then it will be retained and not deleted because there are only eight problem groups available here. In other words, there are not too many variables available for CFA models. The Cronbach's alpha values will be interpreted as the guidelines for each success parameter.

In each problem group of each success parameter, the coefficient alpha values will be computed. If an initial alpha value is less than 0.6, then one or more items will be deleted until a recomputed alpha value is greater than 0.6. The statistical computer program, SPSS®, provides the expected alpha value if an item is deleted. Even though the researcher could delete as many items as he/she wants to satisfy the minimum coefficient values, at least, two items need to be retained in each problem group (Bassioni et al. 2008). After this procedure, the number of items in each problem group of each success parameter will be determined for the next step.

Average values of groups of each success parameter

There will be maximum 43 problems available for eight problem groups after the computation of the coefficient alpha. There is a chance that some success parameters have less than 43 problems. The number of items in each group will vary, depending on the Cronbach's alpha values. So the same concept that is based on the problem groups not the individual problems of canonical correlation is applied to this step. To get the value of each problem group, the average value is computed and applied for each success parameter. After the computation of the Cronbach's alpha, the original value of remaining items will be used for the computation of the average value of each problem group in each success parameter. Eight average values for each success parameter will be available for normality check.

Data normality

There are two major estimation methods in CFA models. They are the Maximum Likelihood (ML) and the Weighted Least Squares (WLS) method. Both of them are popular in CFA models. But the major difference in between these two methods is the data normality. To use ML method, the data should be normal otherwise WLS has to be used for CFA models. As mentioned earlier, there will be a underestimated or overestimated parameter if a wrong estimate method is chosen for a set of data (Brown 2006). Regarding the data normality, there are two

aspects to be addressed. One is skewness and the other is kurtosis. Skewness is a measure of the symmetry of a distribution and kurtosis is a measure of having a peak or flat of distribution (NIST/SEMATECH 2006; Wynne 1982). Skewness mainly refers to the location of the center point of a distribution such as being skewed to the right or being skewed to the left and kurtosis depicts the height of the distribution such as high (peak) or low (flat). The equations for skewness and kurtosis are shown in Table 3-16 and an example distributions of skewness and kurtosis are shown in Figure 3-10.

Table 3-16. Equations for skewness and kurtosis

Skewness	Kurtosis
$skewness = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)s^3}$	$kurtosis = \frac{\sum_{i=1}^{N}(Y_i - Y)^4}{(N-1)s^4}$ or $kurtosis = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4} - 3$

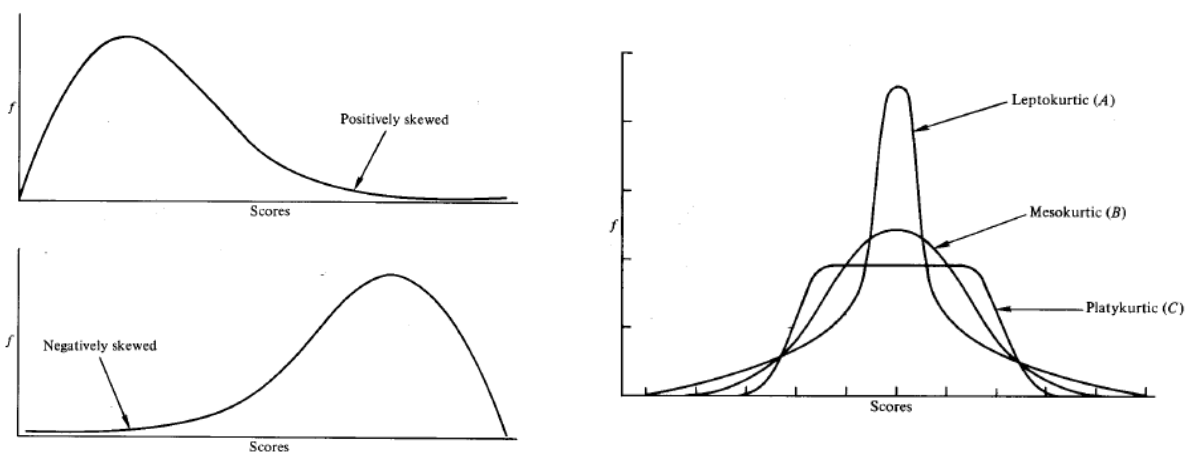
Where,

$\bar{Y}$: Mean

s : Standard deviation

N : Number of data

Source: NIST/SEMATECH 2006



A) Skewness. B) Kurtosis

Figure 3-10. Distributions (Wynne 1982).

If the values of skewness are negative, then the distribution is skewed to the left as shown in Figure 3-10A or vice versa. If Kurtosis has high values, then the distribution is near at the peak, Leptokurtic (A) in Figure 3-10B. A flat form of a distribution may have a low kurtosis value, Platykurtic (C) in Figure 3-10B. To be normal, the values of Skewness and Kurtosis have to be zero or near zero. The range of normal, moderately non-normal, and severely non-normal distributions are defined (Curran et al. 1996). Table 3-17 shows the ranges of Skewness and Kurtosis of each segment.

Table 3-17. Ranges of Skewness and Kurtosis

Segment	Ranges	
	Skewness	Kurtosis
Normal	0 and 2	0 and 7
Moderately Non-normal	2 and 3	7 and 21
Severely Non-normal	Greater than 3	Greater than 21

Source: Curran et al. 1996.

According to Curran et al. (1996), the cutoff for being normal may be too narrow if only the segment of normal is included. It will be too wide if the segment of moderately non-normal is included as normal. So it may be necessary to find another method to check for data normality. To check for data normality in this research, the critical region (CR) method is applied. The data is assumed to be normal if the value of CR falls into greater than -2 and smaller than 2 (SPSS 2008). It clearly addresses the range of cutoff for data normality. The CR values are computed by dividing the Skewness or Kurtosis value by their standard error. These values will be provided by SPSS® and the Amos™ packages. After checking the normality of data, the estimation method will be determined.

Computer package and goodness-of-fit test

This research will use a set of raw data as input for the computer program. There are a couple of computer packages available for CFA models such as LISREL, Amos, SAS, and

Mplus. There is a subtle difference in functions among these computer packages. Each program has different functions, depending upon its version but all these programs are capable to perform this calculation. All the computer software packages discussed earlier allow users to do this parameter estimate. The Amos computer package will be chosen for this research because this package has two options to perform CFA models. One is a traditional syntax input command method and the other is a graphical method. A screen capture of Amos is shown in Figure 3-11.

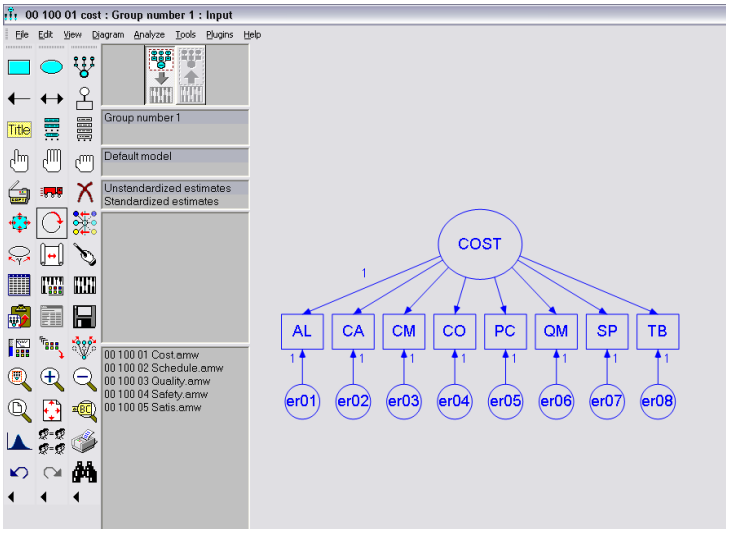


Figure 3-11. Screen capture of Amos

This capture shows an example of a graphical method. Amos is more user-friendly than other programs and gives users more versatility in the usage of the package. This research is to use this graphical method. After running Amos, the goodness-of-fit test will be performed. There are four fit indices for three major categories and it is recommended to use at least four indices from three different categories (Brown 2006). The three categories are Absolute Fit, Parsimony Correction, and Comparative Fit. Each category, its index, and its recommended cutoff values are shown in Table 3-18, including the χ^2 values.

The cutoff values of each index are a little bit subjectively different from authors and articles and also the acceptable ranges of cutoff values are various. Brown (2006) addresses the

role of p value of χ^2 in CFA model as index. The p value would be satisfied, greater than 0.05 at $\alpha = 0.05$ if the cutoff values meet the certain value point or certain ranges and a large number, greater than 300 or more, of samples is available. A large number of samples could lead to a satisfied p value for χ^2. That is why Brown (2006) mentions that the p value is not a good index

Table 3-18. Goodness-of-fit test categories and its indices

Category	Index	Cutoff Value
χ^2	H_0: $\Sigma = S$ H_a: $\Sigma \neq S$ or no restriction Should fail to reject H_0 at $\alpha = 0.05$	> 0.05
Absolute Fit	Standardized Root Mean Square Residual (SRMR)	< 0.08
Parsimony Correction	Root Mean Square Error of Approximation (RMSEA)	< 0.10
Comparative Fit	Comparative Fit Index (CFI)	> 0.95
	Tucker-Lewis Index (TLI)	> 0.95

Source: Brown 2006

and it is recommended to check more indices to compensate for the p value. From this perspective, it is inferred that a CFA model at least has to satisfy the p value first and then other indices. Although all indices are recommended to be addressed in CFA models, the main index has to be the p value of χ^2 and other indices are supplementary to check the models for this research. The number of samples for this research is 100 which is just enough for a CFA model but this is not considered a large number of samples.

If the initial results of Amos do not satisfy the χ^2 value, model trimming will be performed until it satisfies the model fitting criteria. The model trimming is originally designed to delete an unnecessary path in the model to improve the model fitting (Garson 2008c). Any unnecessary path will be defined as statistically insignificant parameter estimate among all parameters in the model. It means any item that fails to reject the null hypothesis (z-value < 1.96, $\alpha = 0.05$) has to be deleted. As shown in Figure 3-8, the CFA model for this research is not complicated and has

a maximum of eight indicator variables. So the concept of model trimming is revised to delete an item (variable) that is less significant than others in the model even though a parameter estimate of that item is statistically significant. Model trimming will be performed until the final revised model satisfies the goodness-of-fit test. A detailed method for deleting variables will be addressed in Chapter 4.

Parameter estimate and significance test

In the previous section, the main concern was a CFA model fitting using the goodness-of-fit test. This is a fitting for a whole model without testing for the statistical significance of an individual variable. If a CFA model satisfies the goodness-of-fit test as a whole model, and then the statistical significance test has to be performed for each individual remaining variable in the model. During the model trimming process, some indicator variables may be deleted to satisfy the goodness-of-fit test. For the remaining indicator variables, each parameter estimate has to be checked. Even though there are some indicators remaining in the model after the model trimming, there is a chance that any indicator may not be statistically significant at $\alpha = 0.05$. The model cannot be finalized until the parameter estimate is completed. During this procedure, the researcher could sort out the finalized indicators in the model and its parameter estimates. All statistical significance test in this research is at $\alpha = 0.05$ unless specified otherwise.

In this chapter, all the strategies and design for this research have been laid out. Major methodologies used for this research are 1) Canonical correlation for relationships between problem groups; 2) EFA for the preliminary stage of CFA; and 3) CFA for the final model. This chapter provides some detailed information on each method and the potential issues are already addressed. Based on this information presented in this chapter, all the outputs of this research will be discussed in Chapter 5, except for canonical correlations that were already discussed in

this chapter. In addition to methodologies presented in this chapter, the methodology for the application of CFA outputs is Simple Multi-Attribute Rating Technique Using Swing Weight (SMARTS). It is briefly reviewed in Chapter 2 and it will be discussed again in Chapter 5.

CHAPTER 4
FACTOR ANALYSIS RESULTS

Overview

The overall strategies and design, including methodologies have been discussed so far. In this chapter, all the results of these addressed methods will be explained. They are the Cronbach's Alpha, Average Value of Group, EFA, Normality Check, and CFA. The workflow for this chapter is shown in Figure 4-1 and the brief discussion of each step will follow.

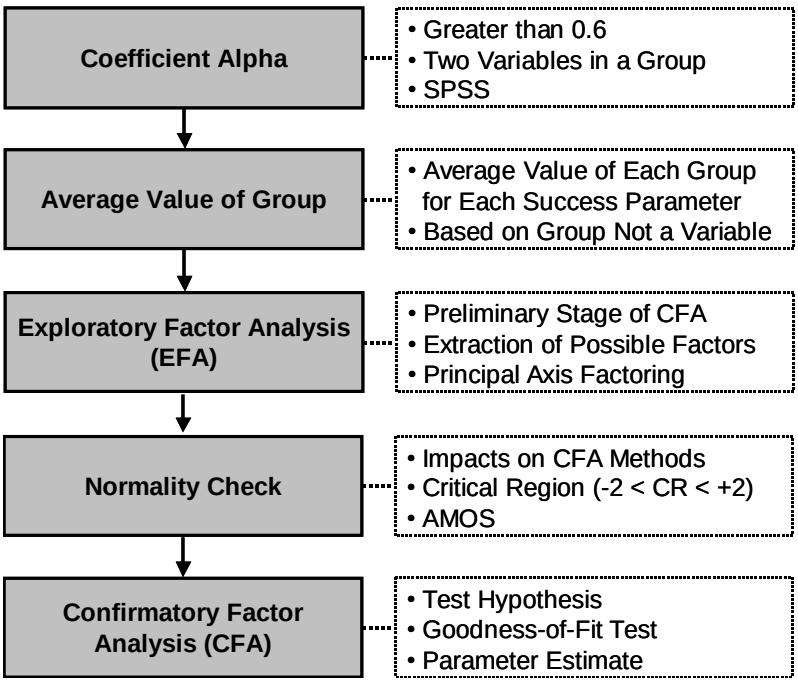


Figure 4-1. The procedure of results

The first step is to determine Cronbach's alpha. The coefficient values have to be greater than 0.6 (Hair et al. 1998) to retain any variables in a group. Even though any variables could be deleted to improve the coefficient values, there have to be at least two variables in a group (Bassioni et al. 2008). The Cronbach's alpha values will be computed using SPSS. The average values for a group will be calculated after the Cronbach's alpha is determined. From this point forward all the value addressed will be the average value of each group for each success parameter. EFA will be performed after the computation of average value of a group as a

preliminary stage of CFA. This is a good process to check how many factors could be extracted before CFA is performed. It will provide the overview of CFA. The method used for EFA is principal axis factoring, using SPSS. The final stage of this chapter is to perform CFA. During this stage, the hypotheses mentioned in Chapter 3 will be tested along with the goodness-of-fit test and the parameter estimate. The program used for CFA is Amos.

Cronbach's Alpha

Initial Cronbach's Alpha Values

The initial Cronbach's alpha values are computed based on 43 problems groups. The computation is completed for each group of each success parameter. There are eight groups available for five different success parameters. This means that the computations will be done at least 40 times (8 groups × 5 success parameters). Table 3-1 Groups of Potential Problems already addresses the number of variables (problems) in each group, so it is not necessary to address it again here. The computation of Cronbach's alpha is done in SPSS. The rules followed by the researcher in this portion of analysis were as follows:

- It is necessary to retain as many problems as possible in a group for the computation of average value and as many groups as it possible for the CFA models.
- If the values of Cronbach's alpha meet the minimum (0.6), then all variables in a group are retained. This rule is applied when the initial value satisfies the minimum and also the coefficient value is greater than 0.6. In this case, all the variables will be retained because the initial value already meets the minimum. If the initial Cronbach's alpha value is smaller than the minimum, some problems are deleted.
- The item deletion process will be stopped when the improved coefficient alpha value meets the minimum.

The computations of coefficient alpha values are based on problems within each group but the results are shown as group. There are eight problem groups available for each project success parameter. If any of problem group does not meet the minimum Cronbach's alpha and

so is completely deleted, a project success may have fewer problem groups than eight (8) for CFA models. As mentioned in Chapter 3, this process will be mainly interpreted as the guidelines for each problem group. Table 4-1 shows the initial results of Cronbach's Alpha.

Table 4-1. Initial results for Cronbach's Alpha

Problem Group	Cost	Schedule	Quality	Safety	Satisfaction
AL	0.776	0.762	0.795	0.823	0.839
CA	0.617	0.512	0.590	0.736	0.779
CM	0.633	0.629	0.671	0.828	0.844
CO	0.451	0.469	0.555	0.585	0.620
PC	0.839	0.784	0.888	0.897	0.900
QM	0.738	0.719	0.643	0.896	0.807
SP	0.881	0.833	0.845	0.559	0.908
TB	0.761	0.737	0.745	0.796	0.737

Some of initial Cronbach's alpha values did not satisfy the minimum as shown in Table 4-1. They are 1) CA in Schedule and Quality; 2) CO in Cost, Schedule, Quality, and Safety; and 3) SP in Safety. The worst case is for group CO. It does not satisfy almost every project success parameter. All these Cronbach's alpha values have to be improved. There are two limitations on improving Cronbach's alpha values. One is a chance that the initial value may be the highest coefficient alpha value. It means that there is no way to improve the initial coefficient alpha value. The other is, as mentioned earlier in this section, is that there are at least two variables remaining in a group.

Improvement of Coefficient Alpha Values

The computations of Cronbach's alpha values are done in SPSS. SPSS provides the user with the expected Cronbach's alpha values when any of items in a group is deleted. It is helpful to decide which item has to be deleted to improve the Cronbach's alpha value. Table 4-2 shows AL for Cost as an example of SPSS output. The initial Cronbach's alpha value of AL for Cost is 0.776, which is greater than 0.6. So it is not necessary to delete any item in that group for

improvement. But the Cronbach's alpha value will be 0.783 which is greater than 0.776 if AL1 is deleted. So it is a guideline map for the improvement of Cronbach's alpha value.

Table 4-2. Example of output of Cronbach's Alpha value in SPSS

AL	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AL1	31.76	22.184	0.231	0.783
AL2	32.37	19.124	0.520	0.745
AL3	33.14	18.728	0.468	0.753
AL4	32.27	19.654	0.508	0.749
AL5	32.46	17.948	0.583	0.733
AL6	32.61	18.806	0.470	0.753
AL7	33.18	16.371	0.619	0.724
AL8	32.47	18.433	0.423	0.764

It is necessary to improve seven problems groups, which are CA in Schedule and Quality, CO in Cost, Schedule, Quality, and Safety, and SP in Safety as shown in Table 4-1. The Cronbach's alpha values of CA in Schedule and Quality and CO in Safety can be improved by deleting some of items in each group. On the other hand, it is impossible to improve the Cronbach's alpha values of CO in Cost, Schedule and Quality and SP in Safety. The initial Cronbach's alpha values are the highest values that be accomplished. The Cronbach's alpha values of CO in Cost and Schedule are 0.451 and 0.469 respectively and the values of CO in Quality and SP in Safety are 0.555 and 0.559 respectively. The first two values are not even close to 0.6 but the latter two values are close enough to 0.6. So the latter two values from CO in Quality and SP in Safety could possibly be retained. The problem occurs with CO in Cost and Schedule. Even though their Cronbach's alpha values are a little bit far from 0.6 but close to 0.5, they have to be retained because there only eight problem groups. If this does not fit to the model, they may be trimmed in CFA models. Therefore, at this stage, these two groups have to be retained. Table 4-3 shows the output of CO in Quality as example of a Cronbach's Alpha value that is impossible to improve.

Table 4-3. Incapability of improvement of Cronbahc's alpha value of SPSS

CO	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CO1	8.41	4.285	0.314	0.527
CO2	8.02	3.212	0.470	0.271
CO3	8.09	3.820	0.321	0.525

The initial Cronbach's alpha value of CO in Quality is 0.555 as shown in Table 4-1 but all potential alpha values after deleting any variable are less than 0.555 if any item is deleted. In this case, it is not necessary to delete any item.

The Cronbach's alpha values of CA in Schedule and Quality and CO in Safety can be improved by deleting some of items in each group. Their initial Cronbach's alpha values are 0.512, 0.590, and 0.585 for CA in Schedule and Quality and CO in Safety respectively. Tables 4-4, 4-5, and 4-6 show how the initial Cronbach's alpha values are able to be improved by using the SPSS output.

As shown in Table 4-4, the initial Cronbach's alpha value can be improved to 0.621 by deleting item CA3. So while the initial value is 0.512 for this problem group, The improved value is 0.621, which is greater than 0.6. The process of improvement has to stop here because the revised value meets the minimum and CA still has three variables remaining, which exceeds the minimum requirement of two variables (Bassioni et al. 2008).

Table 4-4. Improvement of Cronbach's alpha value for CA in schedule

CA	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CA1	14.08	4.054	0.501	0.280
CA2	13.88	4.410	0.425	0.354
CA3	14.79	4.652	0.124	0.621
CA4	15.33	4.244	0.257	0.487

The initial Cronbach's alpha value of CA in Quality can be improved to 0.701 by deleting CA3 as shown in Table 4-5. The improved Cronbach's alpha value of CA in Quality is 0.701

and it meets the minimum value of 0.6. As CA in Schedule, the remaining problems in that group are still three, which is greater than two (Bassioni et al. 2008).

Table 4-5. Improvement of Cronbach's alpha value for CA in quality

CA	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CA1	12.14	6.263	0.520	0.414
CA2	12.77	5.310	0.546	0.361
CA3	12.59	7.820	0.123	0.701
CA4	13.65	6.614	0.356	0.530

The final discussion on improvement of Cronbach's alpha value is shown in Table 4-6. The initial Cronbach's alpha value is 0.585 and the improved Cronbach's alpha value is 0.612 by deleting CO3 to improve. The revised value and the remaining number of problems in a group meet the requirements. All three Cronbach's alpha values are finally improved by deleting one of variables in each group. CA3 has been deleted in Schedule and Quality and CO3 has been deleted in Safety.

Table 4-6. Improvement of Cronbach's alpha value for CO in safety

CO	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CO1	6.74	5.245	0.303	0.605
CO2	6.68	3.291	0.600	0.126
CO3	6.18	4.311	0.316	0.612

Final Cronbach's Alpha Values

Cronbach's Alpha is used to check the degree of consistency of measurement. If the degree of consistency is high, then the measurements will be correlated to each other (Spector 1992). The Cronbach's alpha shows the degree of consistency of measurement. The higher the Cronbach's alpha value is, the higher the consistency is. The initial Cronbach's alpha values can be categorized into three types. One is based on most of the Cronbach's alpha values showing a good consistency, which means meeting the minimum values. Another is that it is necessary to improve Cronbach's alpha values and that they are capable of being improved. The last is that

there is no way to improve their initial Cronbach's alpha values. It indicates that the initial values that do not meet the minimum are the possible highest values. Even though there are lower Cronbach's alpha value groups, it is necessary to retain all possible groups for the CFA models. The Cronbach's alpha will be considered as a guideline for checking its measurement consistency. So no matter what the initial and final coefficient values are, all the groups are intact at this stage for the purposes of this study. Table 4-7 shows the final coefficient value of each group for each project success parameter.

Table 4-7. Final Cronbach's alpha values

Problem Group	Cost	Schedule	Quality	Safety	Satisfaction
AL	0.776	0.762	0.795	0.823	0.839
CA	0.617	0.621	0.701	0.736	0.779
CM	0.633	0.629	0.671	0.828	0.844
CO	0.451	0.469	0.555	0.612	0.620
PC	0.839	0.784	0.888	0.897	0.900
QM	0.738	0.719	0.643	0.896	0.807
SP	0.881	0.833	0.845	0.559	0.908
TB	0.761	0.737	0.745	0.796	0.737

As shown in Table 4-7, the improved values are 0.621, 0.701, and 0.612 for CA in Schedule and Quality and CO in Safety respectively. Except for the groups with lower Cronbach's alpha values, most of the rest show a good consistency of measurement. The highest value is 0.908 for SP in Satisfaction and the second highest is 0.900 for PC in Satisfaction. All eight groups will be retained for the next step of this research.

Average Value of Group

There are 43 problems available for this research. These 43 problems are broken down into eight different groups. The number of problems in a group is different from each other as shown in Table 3-1. Each detailed expression of a problem with its group is found in Appendix A. As mentioned in Chapter 3, from this step, everything is based on the average value of group not values of individual problems. Forty three problems could provide as detailed information as

possible but it is hard to provide an overview of problem group for each project success parameter. One of the objectives of this research is to define the relationships between project problems and their impacts on project success parameters. To achieve this goal, it is more appropriate to use the average value of a group than to use the value of an individual problem, especially dealing with multi-project success parameters. As discussed in Chapter 3, each problem has a different impact on a success parameter such as frequency histogram and canonical correlations. After studying the relationships between problems and project success parameters, using the problem group perspective, then the individual level will be studied later but not in this research because there is not enough data on the multi-project success parameter at the problem group perspective. This research will provide an overview of the relationships between problems and their impacts on project success parameters from the group level and will be a first step for similar future studies.

Another reason for using the average value of a group is related to the method for CFA but not for EFA. It is easier and more reliable to build a CFA model using eight groups than using 43 problems. So the average of each group value will be used for this research and everything will be based on the group level and not on the individual problem. The deleted items like CA in Schedule and Quality for improvement of the Cronbach's alpha value are excluded when the computation of the average value is performed.

Exploratory Factor Analysis (EFA)

Overview

It is not a requirement to perform the EFA before the CFA is developed but it is a good preliminary stage for CFA (Brown 2006; Thompson 2004). The theory or number of factors to be tested could be assumed until the CFA is completed, for example, when only one factor is expected for CFA. If there are two factors extracted using EFA, then CFA should be modified to

a two-factor model instead of one-factor model. On the other hand, if only one factor is extracted by EFA, then the one-factor model will be tested in CFA. P value or other indices in CFA represents how different the degree of gap between the raw data and the CFA model based on a theory is. It will be statistically acceptable when the gap between the raw data and the CFA model is small. That is why it is necessary and beneficial to perform EFA before CFA even though it is not required. For this research, each success parameter is the expected factor because every problem is evaluated in terms of its impact on each success parameter. If only one factor is extracted, then it will be tested using CFA. If not, the model has to be modified. The factor extraction method between EFA and CFA is similar. It means that there is a better chance to get a small gap between the raw data and the CFA model.

Factor Extraction Technique

The factor extraction methods have been addressed in Chapter 3. The two methods are Eigenvalue greater than 1.0 and the Scree test. There are mainly two techniques available in EFA, they are principal component analysis (PCA) and common factor analysis (CFA). Both of them are used for similar purposes of data reduction but the underlying assumptions are different (ACITS 1995). In CFA the variance of each variable is decomposed into common variance that is shared by other variables such as the factor variances in CFA (ACITS 1995). It means that it considers only common variance and has a unique variance for each variable. On the other hand, PCA considers the total variance, which is 1.0 and therefore, there is no distinction between common and unique variance (ACITS 1995). Confirmatory factor analysis (CFA) is based on the common factor analysis (CFA) model addressed in Chapter 3 (Floyd and Widaman 1995). The purpose of EFA for this research is to facilitate the preliminary stage of CFA to explore the construct in the data set. So the technique for EFA factor extraction has to be CFA not PCA.

EFA will have been done using the principal axis factoring technique in SPSS. Principal axis factoring is another name for common factor analysis.

Eigenvalue Greater Than 1.0 Method

One of two factor extraction methods is Eigenvalue greater than 1.0 and it will be discussed in this section. Although there are various options to set up the output of EFA, three options that are communalities, total variance explained, and factor loadings are addressed here. All options to extract factors are set up to Eigenvalue greater than 1.0. Figure 4-2 shows the capture of output of Cost for EFA as an example. In Figure 4-2, communalities are the variances explained by factor for that variance. For example, 0.758 for AL is 75.80% of the AL variance explained. The highest variance explained is PC with 0.799 and the lowest is 0.377 for CO. Figure 4-2 shows that Total Variance Explained table which contains the Eigenvalue of each possible extracted factor, which is the column of Total under Initial Eigenvalues. According to this table, the only factor that has an Eigenvalue greater than 1.0 is Factor 1. It shows that only one factor can be extracted using this method. The Eigenvalue of Factor 1 is 5.301 and the rest of the values are less than 1.0. Then Factor 1 can be named as Cost because this is the

Communalities

	Initial	Extraction
AL	.711	.758
CA	.661	.673
CM	.530	.444
CO	.440	.377
PC	.743	.799
QM	.691	.691
SP	.699	.650
TB	.595	.554

Extraction Method: Principal Axis Factoring.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.301	66.261	66.261	4.947	61.836	61.836
2	.838	10.477	76.738			
3	.483	6.040	82.778			
4	.413	5.159	87.937			
5	.325	4.060	91.997			
6	.249	3.107	95.104			
7	.209	2.619	97.723			
8	.182	2.277	100.000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor
	1
AL	.871
CA	.821
CM	.666
CO	.614
PC	.894
QM	.831
SP	.806
TB	.744

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 5 iterations required.

Figure 4-2. Example of output of EFA for cost

measurement of problem impacts on cost and the only factor extracted. The column of % of Variance shows that the variance explained by that factor out of all potential factors. The Factor 1 is the highest with 66.261% and the second highest is factor 2 with 10.477%. The first extracted factor has the highest Eigenvalue and highest % variance explained and the last extracted factor has the lowest Eigenvalue and lowest % variance explained. This is a partial explanation of why the Eigenvalue has to be greater than 1.0.

The last table in Figure 4-2 shows the factor loading of each variable for the extracted factor, called Factor Matrix. The highest factor loading comes from PC with 0.894 and the lowest loading comes from 0.614. Form this table, it is evident that PC has the highest impact on Cost and CO has the lowest impact on Cost. So from this example, only one factor is extracted in Cost with 66.261% of variance explained. The rest of project success parameters, Schedule, Quality, Safety, and Satisfaction, will be as analyzed similarly to the way Cost has been done. Table 4-8 shows the EFA output summary for Schedule using SPSS.

Table 4-8. EFA summary output of schedule

Factor	Eigenvalues			Factor Loading	
	Total	% of Variance	Cumulative %		
1	5.249	65.616	65.616	AL	0.861
2	0.657	8.208	73.825	CA	0.657
3	0.495	6.191	80.016	CM	0.791
4	0.471	5.889	85.905	CO	0.690
5	0.433	5.418	91.323	PC	0.766
6	0.292	3.655	94.928	QM	0.814
7	0.224	2.795	97.772	SP	0.788
8	0.178	2.228	100.000	TB	0.854

The number of extracted factor using the Eigenvalue greater than 1.0 method is one for Schedule as shown Table 4-8. Only one factor (Factor 1 in Table 4-8) is extracted with an Eigenvalue of 5.249 and its communality (% of variance) is 65.616%. The extracted factor would be named as Schedule because only one factor is extracted and this is a measurement about Schedule. The two columns on the right show the extracted factor's factor loading. The

highest is AL with 0.861 and the lowest is CA with 0.657. AL has the highest impacts on Schedule (Factor 1) and CA has the lowest impact on Schedule (Factor 1). The EFA output summary of Quality, Safety, and Satisfaction is shown in Tables 4-9, 4-10, and 4-11 respectively.

Table 4-9. EFA summary output of quality

Factor	Eigenvalues			Factor Loading	
	Total	% of Variance	Cumulative %		
1	5.411	67.638	67.638	AL	0.869
2	0.605	7.559	75.197	CA	0.707
3	0.564	7.054	82.251	CM	0.817
4	0.480	5.994	88.245	CO	0.736
5	0.364	4.549	92.794	PC	0.877
6	0.266	3.327	96.122	QM	0.635
7	0.165	2.058	98.179	SP	0.815
8	0.146	1.821	100.000	TB	0.876

Table 4-10. EFA summary output of safety

Factor	Eigenvalues			Factor Loading	
	Total	% of Variance	Cumulative %		
1	5.889	73.613	73.613	AL	0.868
2	0.723	9.036	82.648	CA	0.884
3	0.436	5.455	88.104	CM	0.865
4	0.276	3.447	91.551	CO	0.817
5	0.244	3.051	94.601	PC	0.920
6	0.185	2.313	96.914	QM	0.879
7	0.135	1.685	98.599	SP	0.563
8	0.112	1.401	100.000	TB	0.858

Table 4-11. EFA summary output of satisfaction

Factor	Eigenvalues			Factor Loading	
	Total	% of Variance	Cumulative %		
1	6.119	76.484	76.484	AL	0.890
2	0.510	6.374	82.859	CA	0.852
3	0.387	4.834	87.693	CM	0.891
4	0.334	4.172	91.864	CO	0.852
5	0.198	2.477	94.341	PC	0.914
6	0.174	2.175	96.516	QM	0.835
7	0.160	1.999	98.515	SP	0.829
8	0.119	1.485	100.000	TB	0.775

From the summary of EFA output of Quality, Safety, and Satisfaction, it is evident that only one factor (Factor 1 from Table 4-9, 4-10, 4-11) can be extracted using the Eigenvalue greater than 1.0 method for each success parameter. The communality of Safety and Satisfaction is greater than the rest of three project success parameters at 73.613% and 76.484% respectively.

The highest factor loading among three project success parameters comes from PC with 0.877, 0.920, and 0.914 for Quality, Safety, and Satisfaction respectively and the lowest factor loadings among them are different from each other. Even though PC has the highest impact on these three success parameters, the rest of project problem group has different factor loadings on each success parameter. It is clearly shown that each problem group has a different impact on a project success parameter. Using the Eigenvalue greater than 1.0 method, only one factor from each project success parameter could be extracted. As Thompson (2004) indicated no cases exist of Eigenvalues that are right above 1.0 like 1.002 or 1.001 and right below 1.0 like 0.998 or 0.995 when using this method for factor selection. All five project success parameters have clear cutoff Eigenvalues for their factor selection.

Scree Test Method

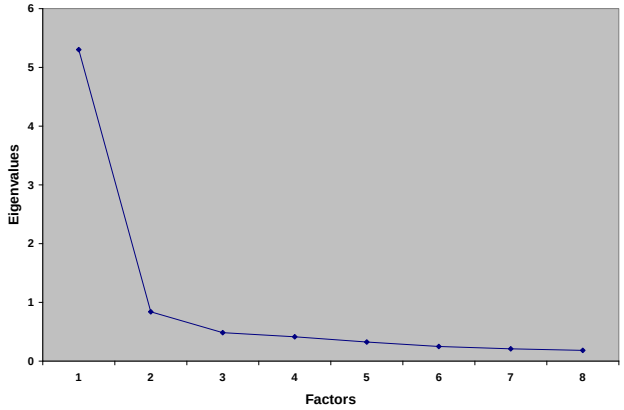
The Eigenvalues depicts the amount of information represented within a given factor (Thompson 2004). The first extracted factor has the highest Eigenvalue and the last extracted factor has the lowest Eigenvalue. "Scree is the rubble of loose rock and boulders not solidly attached to mountains that collects at the feet of the mountains. Cattell thought of solid, big, intact mountains as being analogous to solid, noteworthy factors that researchers should recognize and retain. Trivial factors, however, are analogous to Scree, and should be left behind in the extraction process" (Thompson 2004). Trivial factors show the trend of flattening of slopes in the graph of Eigenvalues and factors. Scree test looks for a spot at where the slope of line starts flattening or changes drastically, such as an elbow, because after the slope changes significantly, there is no big difference in slope among factors. It represents that these are the trivial factors such as Scree in the mountains. Table 4-12 shows the summary of Eigenvalues for all possible factors of each success parameter. The Scree plot for each success parameter will be drawn based on the Eigenvalues shown in Table 4-12. The difference in Eigenvalues between

Factor 1 and Factor 2 for each success parameter is large. It will be visually clearer in the plots than in the tables. Figure 4-3 shows the Scree plot of each success parameter.

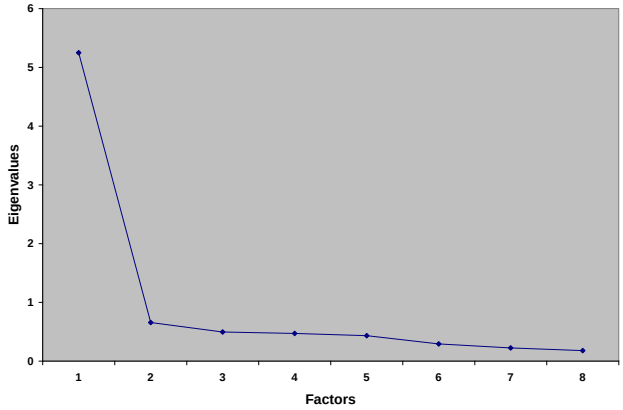
Table 4-12. Summary of Eigenvalues of success parameters

Factor	Success Parameters				
	Cost	Schedule	Quality	Safety	Satisfaction
1	5.301	5.249	5.411	5.889	6.119
2	0.838	0.657	0.605	0.723	0.510
3	0.483	0.495	0.564	0.436	0.387
4	0.413	0.471	0.480	0.276	0.334
5	0.325	0.433	0.364	0.244	0.198
6	0.249	0.292	0.266	0.185	0.174
7	0.209	0.224	0.165	0.135	0.160
8	0.182	0.178	0.146	0.112	0.119

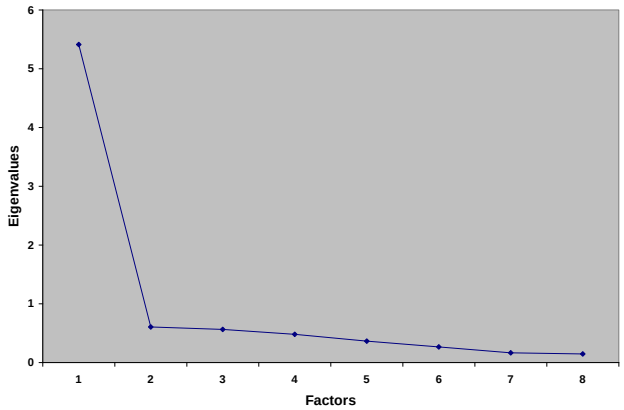
Although the Scree plot of Quality has already been shown in Figure 3-6A, it is presented again as Figure 4-3 for the convenience of discussion and comparison. All five Scree plots for project success parameters clearly show one major pattern or trend in slope change. The largest slope change occurs at Factor 2 in the plot of all parameters. The plot of Cost and Safety has shown a similar change in slope between Factor 1, Factor 2, and Factor 3. Both of them share the similar trend in between Factor 2 and Factor 3 before having less slope change than before. The slope starts more flattened at Factor 3 in Cost and at Factor 4 in Safety. The plot of Schedule, Quality, and Satisfaction shows the same pattern in slope change. There is the largest slope change between Factor 1 and Factor 2. After Factor 2, there is no big difference in slope change between factors. The slope really flattens from Factor 2 to Factor 8. It looks like one horizontal line in the plot. With respect to the Scree test, due to the large slope change, the factor extraction process has to stop at Factor 2. Therefore, the number of extracted factors, using the Scree test, is only one for each project success parameter and slope changes in the plots are very discernible.



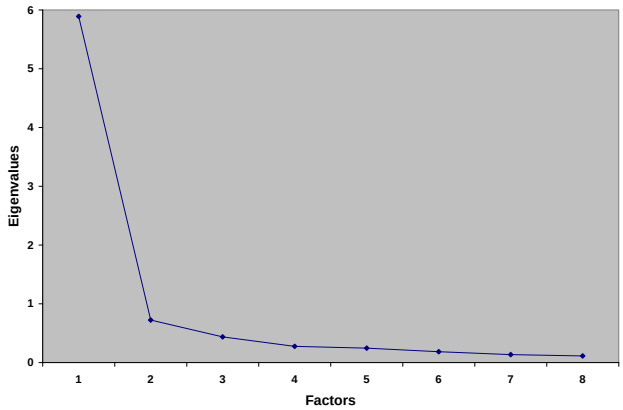
A) Cost



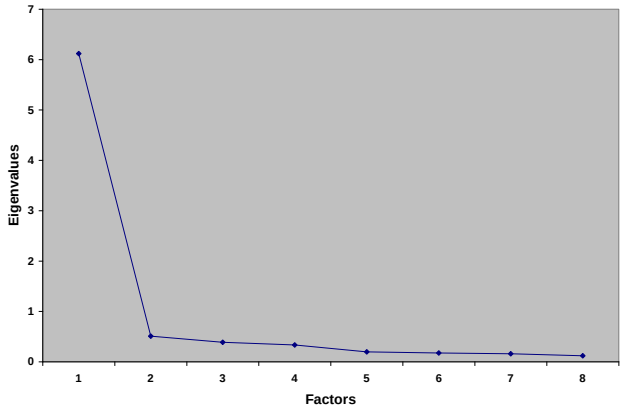
B) Schedule



C) Quality



D) Safety



E) Satisfaction

Figure 4-3. Scree plot.

EFA Result Summary

As the preliminary stage of CFA, the factor extraction has been performed, using EFA. The two methods used for the factor extraction are Eigenvalue greater than 1.0 and Scree test. Both methods rely on Eigenvalues because the Eigenvalue is an index of information of a factor (Thompson 2004). The first method depends upon a numerical output such as greater than or less than 1.0 and the latter one is visually inspected such as the spot where the largest slope change occurs at. Through the EFA factor selection process using two methods, it is concluded that the only one factor could be extracted from each project success parameter. It is a good sign for the positive output of CFA models later in this chapter because as mentioned earlier, the basic mechanism of EFA and CFA are the same.

Normality Check

This is the last preparation step for CFA models. In this section, the normality check of data set will be performed. It will be helpful to decide the method for CFA models. There are two major methods available. One is ML and the other is WLS. The ML method will be used if the data set is normally distributed. WLS will be preferable when the data set does not meet the normality check. The decision on whether to choose ML or WLS depends upon the range of the critical region. To meet the normality check, the CR range has to fall into between -2 and 2 (SPSS 2008). The computation of CR values is done by using Amos and Tables 4-13, 4-14, 4-15, 4-16, and 4-17 show the output of CR values for Cost, Schedule, Satisfaction, Quality, and Safety respectively. Each table has the minimum and the maximum value for each problem group and the value of problem group for skewness and kurtosis and its CR values. All the values shown in the tables in parentheses are negative or less than zero.

The outputs of five different project success parameters can be categorized into two groups. The first group consists of Cost, Schedule, and Satisfaction and the second group consists of

Quality and Safety. As shown in Tables 4-13, 4-14, and 4-15, the CR ranges for skewness of the first group are less than -2. For skewness, the lowest CR value is -6.619 and the highest CR value is -2.232. Even though the CR values of kurtosis are better than those of skewness, they are mostly still out-of-range. So the method of CFA for these groups will be WLS.

Table 4-13. Output of normality check for cost

Variable	Min.	Max.	Skew	CR	Kurtosis	CR
AL	2.250	5.875	(0.752)	(3.071)	1.422	2.903
CA	2.500	6.000	(1.621)	(6.619)	3.853	7.865
CM	3.500	6.000	(0.645)	(2.635)	0.211	0.431
CO	3.333	6.000	(0.888)	(3.624)	1.192	2.434
PC	2.625	5.875	(1.287)	(5.254)	2.635	5.379
QM	2.200	5.800	(1.112)	(4.538)	2.888	5.894
SP	1.286	5.714	(0.770)	(3.143)	0.951	1.940
TB	1.500	5.750	(1.209)	(4.937)	2.840	5.798

Table 4-14. Output of normality check for schedule

Variable	Min.	Max.	Skew	C.R.	Kurtosis	C.R.
AL	2.750	5.750	(0.582)	(2.376)	0.383	0.783
CA	2.000	6.000	(1.499)	(6.120)	3.838	7.834
CM	3.250	6.000	(0.646)	(2.639)	0.126	0.258
CO	2.667	6.000	(0.989)	(4.039)	1.484	3.029
PC	3.250	6.000	(1.253)	(5.116)	1.771	3.616
QM	2.400	5.800	(0.863)	(3.523)	1.256	2.564
SP	1.571	5.571	(0.681)	(2.781)	0.655	1.337
TB	1.500	5.750	(1.272)	(5.195)	2.832	5.780

Table 4-15. Output of normality check for satisfaction

Variable	Min.	Max.	Skew	C.R.	Kurtosis	C.R.
AL	3.000	6.000	(0.598)	(2.440)	(0.323)	(0.659)
CA	2.250	6.000	(1.000)	(4.081)	0.344	0.701
CM	1.500	6.000	(1.051)	(4.290)	0.974	1.988
CO	2.333	6.000	(0.547)	(2.232)	(0.129)	(0.263)
PC	2.250	5.875	(0.904)	(3.689)	(0.021)	(0.043)
QM	2.000	5.800	(0.718)	(2.933)	0.199	0.407
SP	2.000	6.000	(0.981)	(4.006)	0.340	0.694
TB	2.500	6.000	(0.719)	(2.936)	0.212	0.433

The method for Cost, Schedule, and Satisfaction has been determined as WLS. As shown in Table 4-16 and 4-17 for Quality and Safety respectively, the values of CR for skewness are mostly in between -2 and 2. Four out of eight problem groups in Quality and seven out of eight groups in Safety are in this range. Even though the number of CR values in that range in

skewness of Quality is a little bit higher than that of Safety, only one group has an out-of-range CR value for kurtosis as shown in Table 4-16. Regarding CR values for kurtosis, both of them fall in the normal range except for only one group, which is CM in Quality with CR value of 2.488. So it is recommended to use ML method for CFA.

Table 4-16. Output of normality check for quality

Variable	Min.	Max.	Skew	C.R.	Kurtosis	C.R.
AL	2.125	5.875	(0.623)	(2.542)	0.267	0.544
CA	1.000	6.000	(0.602)	(2.456)	0.557	1.136
CM	1.250	5.750	(0.699)	(2.854)	1.219	2.488
CO	2.000	6.000	(0.284)	(1.160)	(0.467)	(0.953)
PC	1.500	5.750	0.102	0.415	(0.408)	(0.833)
QM	3.400	6.000	(0.359)	(1.467)	(0.338)	(0.690)
SP	1.286	5.714	(0.307)	(1.253)	(0.441)	(0.901)
TB	1.250	6.000	(0.685)	(2.795)	0.509	1.039

Table 4-17. Output of normality check for safety

Variable	Min.	Max.	Skew	C.R.	Kurtosis	C.R.
AL	1.500	5.750	(0.405)	(1.655)	(0.110)	(0.224)
CA	2.000	5.250	(0.398)	(1.625)	(0.776)	(1.583)
CM	1.000	5.000	(0.188)	(0.768)	(0.786)	(1.605)
CO	1.000	5.000	(0.310)	(1.264)	(0.593)	(1.211)
PC	1.000	4.750	(0.119)	(0.485)	(0.724)	(1.477)
QM	1.000	5.200	0.044	0.178	(0.783)	(1.598)
SP	4.429	6.000	(0.534)	(2.179)	(0.636)	(1.297)
TB	1.000	6.000	(0.421)	(1.721)	(0.344)	(0.702)

In this section the normality check of the data set for CFA models using Amos and CR range values was addressed. For the project success parameters of Cost, Schedule, and Satisfaction, WLS is the optimal option to use for CFA models because most of their CR values for skewness and kurtosis are out of range to be considered as normal. In this case WLS is suitable for CFA. On the other hand, for Quality and Safety, the CR values for skewness and kurtosis are mostly in between -2 and 2. So it is acceptable to use the ML method for the CFA model.

Confirmatory Factor Analysis (CFA)

Overview

All the procedures addressed in this chapter so far were in preparation for this section. The Cronbach's alpha values have shown the consistency of the data and some of items were deleted to improve the Cronbach's alpha values. Based on the results of Cronbach's alpha, EFA has been performed to extract possible factors before CFA, using the Eigenvalue greater than 1.0 and Scree test method. Outputs of EFA support one factor model for the equivalent CFA model of each project success parameter. Finally, the normality check of data helps decide the method for CFA models like WLS for Cost, Schedule, and Satisfaction and ML for Quality and Safety. The main focus of this section is how well a latent factor (each project success parameter) is manifested by eight problem groups. If they are, then what is the degree of impact of each problem group on each success parameter? If not, how many problem groups are related to a latent factor? And then what are the impacts of each related problem group on each success parameter? In this section, the more detailed information on CFA models will be discussed in the following order: interpretation of the parameter estimate process; initial results; model trimming, and final results.

Interpretation of Parameter Estimate Process

There are two terminologies available for any CFA model in the parameter estimate process. One is the raw estimate and the other is the standard estimate. All the parameter estimates found in articles are normally standard estimated (Garson 2008c). The difference between a raw estimate and a standard estimate is the base. The raw estimate is based on one of variables in the model and the standard estimate is based on the latent factor. The mechanism for computation of the parameter estimate is to compute the raw estimate first and then the raw estimate will be converted into standard estimate. Each unique variance will be computed based

on the standard estimate. To compute the raw estimate, the researcher has to choose or the computer program automatically chooses one variable as a base of the computation for the parameter estimate as shown in Figure 4-4. Even though this notation is based on Amos, the notation graphic may vary among different computer software packages.

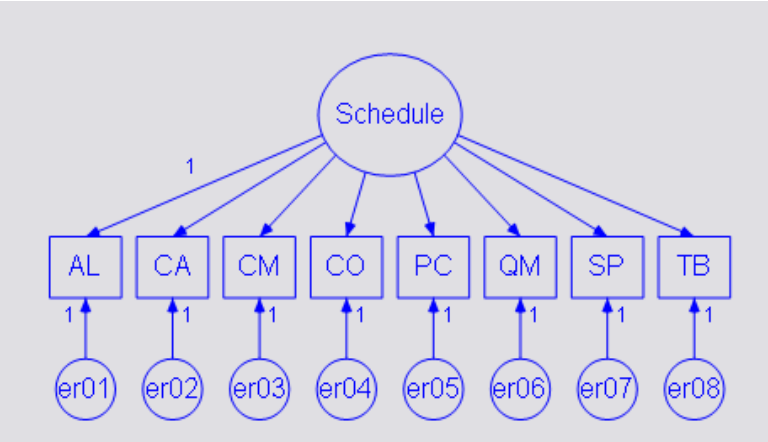


Figure 4-4. Example of graphical input for CFA model

The latent factor in Figure 4-4 is Schedule and it has eight different problem groups. Each problem group has its own unique variance denoted as er01, er02, ……., er08. The "1" in the path in between a latent factor (Schedule) and a group (AL) indicates that the raw estimate will be calculated based on AL. If the value of "1" is on the path between Cost and SP, then it indicates that the raw estimate will be based on SP. So the value of "1" shows the base variable for the computation of the raw estimate in the graphical model. The value of "1" on the path between problem a group and its unique variance is interpreted as the path between a latent factor and each problem group. The raw estimate and the unique variance are tested for their statistical significance using the p value and critical ratio (CR) but the standard estimate does not have them. Regarding the statistical significance test and critical ratio, they can be different depending on how the base is chosen. Tables 4-18 and 4-19 show examples of statistical difference based on the base.

Table 4-18. Example of statistical significance of schedule using AL as base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
AL	←	Schedule	1.000			
CA	←	Schedule	0.633	0.181	3.499	***
CM	←	Schedule	0.982	0.082	11.962	***
CO	←	Schedule	1.010	0.120	8.452	***
PC	←	Schedule	0.770	0.078	9.878	***
QM	←	Schedule	1.169	0.082	14.265	***
SP	←	Schedule	1.229	0.069	17.711	***
TB	←	Schedule	1.071	0.070	15.313	***

Table 4-19. Example of statistical significance of schedule using CA as base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
AL	←	Schedule	1.580	0.452	3.498	***
CA	←	Schedule	1.000	----	----	----
CM	←	Schedule	1.551	0.382	4.060	0.002
CO	←	Schedule	1.596	0.518	3.083	0.002
PC	←	Schedule	1.217	0.388	3.137	***
QM	←	Schedule	1.847	0.531	3.477	***
SP	←	Schedule	1.943	0.587	3.310	***
TB	←	Schedule	1.692	0.495	3.419	***

The parameter estimate method is WLS and is done using Amos. The estimate shown in both tables are raw estimates. The statistical significance values shown in Table 4-18 are based on AL and those shown in Table 4-19 are based on CA. As shown in both tables, the statistical significances are different from the base such as the column of standard error and critical ratio (CR). To be statistically significant, the critical ratio (CR) has to be greater than 1.96 at $\alpha = 0.05$. The values in the "P Value" column shown as '***' represent that the p value is too small to be presented in the table. The critical ratio (CR) is computed by dividing estimate by its standard error and it will be the main index in the model trimming process. Even though the raw estimates are different from each other based on the base variable, the standard estimate, as shown in Table 4-20, is the same.

Table 4-20. Example of standard estimate

Problem Groups			Estimate
AL	←	Schedule	0.837
CA	←	Schedule	0.491
CM	←	Schedule	0.910
CO	←	Schedule	0.730
PC	←	Schedule	0.729
QM	←	Schedule	0.902
SP	←	Schedule	0.820
TB	←	Schedule	0.838

The major difference between Table 4-18, 4-19 and 4-20 in the parameter estimates is that the first two tables are based on one of any variables in the model and the last one is based on the latent factor. That is why the standard estimate has to look for the interpretation of CFA models. The unique variances will be computed based on the standard estimate. So there is no change in statistical significance test of unique variances for each variable no matter what a variable is selected as a base. For this research, AL will be the base of the computation of raw estimate for the initial run and then standard estimate will be computed using Amos.

Initial Results for Each Success Parameter

Before discussing the initial results of the CFA models for each success parameter, the goodness-of-fit-test has to be addressed. The CFA models will be evaluated based on how well they represented the data set in the form of the CFA models (Brown 2006). The goodness-of-fit test is a part of that process. As shown in Table 3-18, to be an acceptable model, the null hypothesis fails to reject the hypothesis, using χ^2 at $\alpha = 0.05$ first and all other goodness-of-fit indices will be explained later in this chapter. To fail to reject the null hypothesis, the p value for each CFA model has to be greater than 0.05 at $\alpha = 0.05$. If not, it will reject the null hypothesis, which means the CFA model is different from the data. Each CFA model of success parameter is shown in Figure 3-8 and a CFA model for Schedule is shown in Figure 4-4. Using these

models, all five initial results of p values of CFA model for success parameters are summarized in Table 4-21.

Table 4-21. Initial results of P values of CFA model

Item	Success Parameters				
	Cost	Schedule	Quality	Safety	Satisfaction
Method	WLS	WLS	ML	ML	WLS
P Value	0.007	0.001	***	***	0.002

The p values of Quality and Safety are written as '***' because the values are too small to be written using three decimal places. All five CFA models' p values are smaller than 0.05. It represents that the null hypothesis has to be rejected at $\alpha = 0.05$. The models and the data are statistically different at this alpha level. In this case, it is not necessary to look for the parameter estimate (factor loading) because there is a significant difference between model and data. In the previous section, the results of EPA have clearly shown that there is only one possible extracted factor in each success parameter using the Eigenvalue greater than 1.0 and Scree test methods. The range of communality of each extracted factor is from 65% for Schedule to 76% for Satisfaction. It indicates that each extracted factor contained information worth 65% through 75%, compared to the original data. The unexplained and remaining 35% and 24% of communality after extracting factors may affect the results of the CFA model because, in general, the CFA model has more parsimonious form than the EFA model in terms of the number of factors and factor loadings, etc (Brown 2006). Then what does the rejection of null hypothesis mean? This could be summarized as follows:

- The number of latent factors would be only one (1) whether it is EFA or CFA. With respect to the parsimonious form of CFA, there cannot be more than one latent factor in CFA models. EFA outputs already show the possible extracted number of factors.

- Each success parameter has not been manifested by eight problem groups. Some of problem groups are not significant enough to fail to reject the null hypothesis of the model.

The main hypothesis of this research addressed in the previous section is that "Each success parameter is manifested by eight problem groups" and, according to the summary above, this hypothesis has to be rejected for all five project success parameters. It indicates that each project success parameter has some problem groups, which are less consistent than the others on the degree of impact using CFA models. It is another benefit of the usage of CFA models to choose better variables. It is sometimes hard to select some variables among a group of variables in a reasonable way. The average value and ranking by summation could be used the most for the selection, but the cutoff values or the range will be based on the personal or groups opinion to choose. In terms of this, the CFA model is useful to filter the variables.

From the discussion above, all p values make the null hypothesis rejected for five CFA models. It is evident that each project parameter has not been manifested by eight problem groups. It is necessary to trim the CFA models to find the variables that are more consistent than others among the eight problem groups in satisfying the statistical significance test.

CFA Model Trimming

Overview

As mentioned earlier, it is necessary to trim the CFA models. This process will be a filtering process to find any problem groups that affect the failure to reject the null hypothesis and also be a process to choose the best fitted model for each success parameter. Those problem groups will be removed from the CFA models. There are two ways to find out the best-fitted model. One is using critical ratio (CR) and the other is using a combination of each problem group to form a model with less than eight variables per CFA model.

Garson (2008c) addresses the usage of critical ratio (CR) for improvement of model fitting. Deleting a statistically insignificant path in the model can improve the model fitting. The value of the critical ratio (CR) is found by dividing the parameter estimate by its standard error. The

cutoff value is 1.96 at $\alpha = 0.05$. Any paths with critical ratio (CR) value less than 1.96 will be removed from the model. But for this research, the CFA models are not that complicated and have only a maximum of eight variables for each success parameter. So this concept will be revised as deleting any variables that are statistically insignificant or less significant than others when all variables are significant until the null hypothesis fails to be rejected. But the critical ratio (CR) will change depending upon what base is set up for each model as shown in Tables 4-18 and 4-19. So the critical ratio (CR) method will be performed, using eight possible models for each success parameter and each model will have a different base. The other method is generating all possible combinations of problem groups consisting of seven variables or less in the model until the null hypothesis fails to be rejected. The first method is deleting any variables in the model to improve model fit. On the other hand, the second method is to find the best fitted model using all possible combinations of problem groups. Since the CFA model for the eight problem groups fails to be rejected, the maximum number of problem groups in the model will be seven. Due to the all possible number of combination models for seven or less problem group for each CFA model, this is a time consuming process, compared to the critical ration (CR) method. For example there are eight possible combinations that consist of seven problem groups for each success parameter and there are 28 possible combinations that consist of six problem groups for each success parameter. A combination of six problem groups will be performed only if there is no best fitted model within seven problem groups of combination. A total number of combinations of five problem groups for each success parameter will have more than those of the seven and six problem groups.

Deleting any variables in the model will stop when the p value is greater than 0.05 in a different base model, using the critical ratio (CR) method. All combination methods will

generate all possible models with the seven problem groups first, and then six problem groups only if there is no combination to meet the p value greater than 0.05 with seven problem groups. The selection of best-fitted model for both methods is based on the p value and number of problem groups retained in the model. In the best-fitted model selection, the first priority among fitted models is any model with the highest p value and the largest number of problem groups retained. The second priority is any model with the minimum satisfied p value and the largest number of problem groups retained. For example, there are two models available having the same p value but a different number of problem groups retained. One has seven problem groups and the other has six problem groups in the model. Then the best-fitted model would be the model with the seven problem groups. In most cases, any model with the largest number of problem groups and that has satisfied the p value would be chosen for the best fitted model because the model would be better fitted when there are less variables in the model.

Critical ratio (CR) method

The values of the critical ratio are different from the base of each CFA model. Eight different CFA models with a different base are expected. For example, using AL as a base, the model will be tested until the p value is greater than 0.05. During this process, a problem group that is not statistically significant will be deleted to improve the model fit. If all values of the critical ratio (CR) are significant, then a problem group that is comparatively less significant than other problem groups will be removed from the model. To be statistically significant, the critical ratio (CR) values have to be greater than 1.96 at $\alpha = 0.05$. Once the best-fitted model has been found, then this process stops for a base and the same procedure is repeated using a different base at a time and so forth. Table 4-22 shows the results of this procedure for Schedule.

Table 4-22. Summary of critical ratio (CR) procedure for schedule

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
AL	0.001	CA	***	CO	***	PC	***	CM	0.195
CA	0.001	CO	0.001	PC	0.001	QM	0.040	SP	0.316
CM	0.001	CA	***	CO	***	QM	0.020	PC	0.034
CO	0.001	CA	***	CM	0.022	PC	0.220		
PC	0.001	CA	***	CO	***	QM	0.020	CM	0.899
QM	0.001	CA	***	CM	0.022	PC	0.220		
SP	0.001	CA	***	CO	***	QM	0.020	CM	0.899
TB	0.001	CA	***	CO	***	QM	0.020	PC	0.034

The first column on the left shows the base of each model. It means that for Schedule there are eight models available. The '***' in the 'P Value' column indicates that the p value is too small. The column 'Del. Var' the variable that was deleted to improve the model fit. The column heading 'First' represents the initial output with eight problem groups. For example base AL, the p value is 0.001 at the first output and CA is deleted to improve the model fit. The critical ratio (CR) value of CA could be statistically insignificant or less significant than that of others'. Now there are only seven problem groups available in the model after the first output using AL as a base because CA has been removed from the model. 'Second' means that the model was run with seven variables here without CA. The p value without CA is too small as shown '***' and CO is chosen to be deleted to improve the model fit and is deleted. So far, CA and CO are removed from the model. The column 'Third' means that the model was run with six variables, i.e without CA and CO. The p value is still too small and PC is chosen to be deleted and is deleted. In column 'Fourth' there are five problem groups available due to the elimination of CA, CO, and PC. After the model is run with five variables, the p value is still small and CM is selected to be removed and is removed from the model. Finally, column 'Fifth' means that the model retains only four variables after the deletion of CA, CO, PC, and CM consecutively and the p value of this model is finally 0.195 which is greater than 0.05. The model improvement

process stops here using AL as the base. The rest of models using different bases such as CA, CM, CO, PC, QM, PC, SP, and TB will repeat the same procedure as described above. To select the best-fitted models among all tested models, the p value has to be greater than 0.05 and the model has to retain as many problem groups as it possible. According to this process, the models using bases of CM and CO were chosen for the best-fitted model and the results for both models are the same in terms of p value and deleted problem groups. Their p value is 0.220 and there are five remaining problem groups (AL, CO, QM, SP, and TB) in the model. The p value is the highest value and, at the same time, the largest number of problem groups retained among all tested models. Even though p values of model with bases of CA, PC, and SP are higher than that of CO and CM, these models have only four problem groups remaining not five. These models have reached the required level of p values after four problem group eliminations. That is why the model with a base of CO and CM is chosen for the best-fitted model. For Schedule, using AL as base, the overall procedures to find the best-fitted model discussed previously are followed. The rest of models using different bases will follow the same procedures. A summary of the critical ratio (CR) method for each project success parameters excluding Schedule is shown in Appendix D. The final selected best-fitted model for each project success parameter is shown in Table 4-23.

Table 4-23. Summary of best-fitted model using critical ratio (CR) method

Success Parameter	P Value	Problem Groups			
		Retained		Deleted	
Cost	0.065	AL, CA, CM, CO, PC, QM, and SP	(7)	TB	(1)
Schedule	0.220	AL, CO, QM, SP, and TB	(5)	CA, CM, and PC	(3)
Quality	0.061	AL, CM, CO, PC, and TB	(5)	CA, QM, and SP	(3)
Safety	0.067	AL, CA, CM, CO, PC, and QM	(6)	SP and TB	(2)
Satisfaction	0.251	AL, CA, CM, CO, and PC	(5)	QM, SP, and TB	(3)

All the p values of selected models are greater than 0.05. The highest is 0.251 for Satisfaction and the lowest is 0.065 for Cost. The minimum retained number of problem groups

is five for Schedule, Quality, and Satisfaction. The maximum retained number of problem groups is seven for Cost. Safety has six remaining problem groups in the model. According to the critical ratio (CR) method, each success parameter is manifested by the remaining problem groups. The deleted problem groups may affect the model fitting of the original eight-problem group model. The critical ratio (CR) method was originally intended to delete a path that is not significant but has been revised to delete a problem group that is not significant or less significant than others. With respect to this revision, it does not seem that it is a good index to find the best-fitted model. One of the reasons is that most of time the p value does not improve whenever a problem group is removed from the model. There is a significant improvement after three or more problem groups have been deleted. Before that point, it is hard to notice the improvement of model. The revision of the concept of critical ratio (CR) method may not apply effectively to this process. It may be necessary to check all possible combinations of problem groups for the best-fitted model of each success parameter with different numbers of problem groups.

All possible combination of problem groups method

There are originally eight problem groups per project success parameter. If each CFA model for success parameter has seven problem groups, all possible combination of seven or less problem groups will be computed using Equation 4-1 (Weisstein 2009a) below.

$$ {}_{n}C_{k} \equiv \binom{n}{k} \equiv \frac{n!}{k!\,(n-k)!}, \qquad \text{(Equation 4-1)} $$

The total number of sets is *n* and the number of possible combination is *k* out of *n*. If each model has seven problem groups then the total number of combination will be 8 (8!/[7!(8-7)!]) for each success parameter. On the other hand, if any CFA model has six problem groups, then the total number of possible combination will be 28 (8!/[6!(8-6)!]). The total number of

combinations will become larger and larger as the number of problem groups gets smaller and smaller. All models with seven problem groups will be tested first and then the process will continue with six or less problem groups when any model cannot fit into seven variables. The selection of best-fitted model is the same as the critical ratio (CR) method. The p value of model has to be greater than 0.05 and contain the largest number of problem groups in the model.

First of all the seven problem groups are tested. It has a total of eight-combination model for each success parameter. Table 4-24 shows the summary of all combinations of seven problem groups of each success parameter. The upper part of table shows the original eight problem groups and the combination of seven problem groups for each success parameter. Each combination is labeled as combination 1 through 8. The lower part of table shows the p values of the counterpart of each combination model for each success parameter. If the p value is too small to present, it will be shown as "***" in the table.

Table 4-24. Summary of combinations of seven problem groups

Original	Combinations							
	1	2	3	4	5	6	7	8
AL		AL	AL	AL	AL	AL	AL	AL
CA	CA		CA	CA	CA	CA	CA	CA
CM	CM	CM		CM	CM	CM	CM	CM
CO	CO	CO	CO		CO	CO	CO	CO
PC	PC	PC	PC	PC		PC	PC	PC
QM	QM	QM	QM	QM	QM		QM	QM
SP	SP	SP	SP	SP	SP	SP		SP
TB	TB	TB	TB	TB	TB	TB	TB	
Success Parameter	P Values							
Cost	0.011	0.005	0.189	0.003	0.004	0.015	0.092	0.065
Schedule	0.005	***	0.079	0.001	0.004	0.054	0.188	0.027
Quality	0.006	0.001	***	***	0.129	***	0.010	***
Safety	0.001	***	***	***	***	***	***	0.002
Satisfaction	0.089	0.001	0.002	***	0.003	0.001	0.004	0.040

Regarding the combination 1, it excludes AL and has all eight problem groups. Its p values are 0.011, 0.005, 0.006, 0.001, and 0.089 for Cost, Schedule, Quality, Safety, and Satisfaction respectively. The combination 2 through 8 would be interpreted similar to

combination 1. The highest p value of each success parameter is 0.189, 0.188, 0.129, 0.002, and 0.089 for Cost, Schedule, Quality, Safety, and Satisfaction respectively. Only the p value of Safety is less than 0.05 and others satisfy the minimum of 0.05. The best-fitted model for Cost would be the combination 3 with the p value of 0.189 that is the highest even though the p value of combination 7 and 8 is greater than 0.05. The best-fitted model for Schedule would be the combination 7. The p values of combinations 3 and 6 are greater than 0.05 but less than that of combination 7. Quality has the only one combination that has the p value greater than 0.05 so combination 5 is the best-fitted model for Quality. The best-fitted model for Satisfaction is the combination 1 with the p value of 0.089 that is the only one p value greater than 0.05. Unfortunately there is no best-fitted model for Safety, using the seven problems in combination. It is evident that Safety has to look at six-problem groups combination to find the best-fitted model. So far there are seven problem groups per model available for Cost, Schedule, Quality, and Satisfaction using the combination method.

The best-fitted model is found for Cost, Schedule, Quality, and Satisfaction using seven-problem groups combination. There is no best-fitted model using seven-problem groups combination for Safety and so it is necessary to find a six problem groups combination for Safety if possible. A total number of possible six-problem groups combinations is 28 as indicated earlier. The results of 28 combinations for Safety are shown in Table 4-25. Each row shows a combination with its p value. The p value will be "***" if it is too small to be presented.

The combination 22 has the highest p value among 28 combination models. This model does not include AL and TB. The second highest is 0.130 from the combination 16 without CA and TB. So the best-fitted model for Safety is the combination 22 with the problem groups of CA, CM, CO, PC, QM, and SP. Using all possible combination methods, the best-fitted model

Table 4-25. Summary of six problem groups combinations for safety

Original		AL	CA	CM	CO	PC	QM	SP	TB	P Value
Combinations	1	AL	CA	CM	CO	PC	QM			0.067
	2	AL	CA	CM	CO	PC		SP		0.002
	3	AL	CA	CM	CO	PC			TB	***
	4	AL	CA	CM	CO		QM	SP		0.003
	5	AL	CA	CM	CO		QM		TB	***
	6	AL	CA	CM	CO			SP	TB	0.112
	7	AL	CA	CM		PC	QM	SP		***
	8	AL	CA	CM		PC	QM		TB	***
	9	AL	CA	CM		PC		SP	TB	***
	10	AL	CA	CM			QM	SP	TB	***
	11	AL	CA		CO	PC	QM	SP		***
	12	AL	CA		CO	PC	QM		TB	***
	13	AL	CA		CO	PC		SP	TB	0.004
	14	AL	CA		CO		QM	SP	TB	0.004
	15	AL	CA			PC	QM	SP	TB	***
	16	AL		CM	CO	PC	QM	SP		0.130
	17	AL		CM	CO	PC	QM		TB	***
	18	AL		CM	CO	PC		SP	TB	***
	19	AL		CM	CO		QM	SP	TB	***
	20	AL		CM		PC	QM	SP	TB	***
	21	AL			CO	PC	QM	SP	TB	***
	22		CA	CM	CO	PC	QM	SP		0.147
	23		CA	CM	CO	PC	QM		TB	0.004
	24		CA	CM	CO	PC		SP	TB	0.003
	25		CA	CM	CO		QM	SP	TB	0.001
	26		CA	CM		PC	QM	SP	TB	***
	27		CA		CO	PC	QM	SP	TB	0.001
	28			CM	CO	PC	QM	SP	TB	0.079

for each success parameter has been found. Table 4-26 shows the final results of all combination methods. Cost, Schedule, Quality, and Satisfaction have seven problem groups in the model and Safety has six problem groups in the model. AL was removed from the initial model twice in total from Safety and Satisfaction. Other removed problem groups have been removed only once.

Table 4-26. Summary of best-fitted model using possible combination method

Success Parameter	P Value	Problem Groups			
		Retained		Deleted	
Cost	0.189	AL, CA, CO, PC, QM, SP, and TB	(7)	CM	(1)
Schedule	0.188	AL, CA, CM, CO, PC, QM, and TB	(7)	SP	(1)
Quality	0.129	AL, CA, CM, CO, QM, SP, and TB	(7)	PC	(1)
Safety	0.147	CA, CM, CO, PC, QM, and SP	(6)	AL and TB	(2)
Satisfaction	0.089	CA, CM, CO, PC, QM, SP, and TB	(7)	AL	(1)

Critical ratio (CR) vs. all possible combination

There are two methods that can be used to find the best-fitted model for each success parameter because the original eight-problem group model rejects the null hypothesis. The two methods are the critical ratio (CR) method and the all possible combinations method. The first one is to revise to apply the concept and the second one is to perform all possible combinations of problem groups. The critical ratio (CR) method stops the model trimming once a model is found to satisfy the p value, using a different base, no matter how many problem groups are available in the model. The final selection for the best-fitted model is performed among trimmed models of different bases. On the other hand, the all possible combination method tests all possible combination models in terms of seven-problem groups first and then six-problem group or less than that until the model is found to satisfy the p value. Table 4-27 shows the comparisons between these two methods.

Table 4-27. Comparisons of critical ratio and all possible combination

Success Parameter	Critical Ratio		All Possible Combination	
	P Value	# of Remaining Problem Groups	P Value	# of Remaining Problem Groups
Cost	0.065	7	0.189	7
Schedule	0.220	5	0.188	7
Quality	0.061	5	0.129	7
Safety	0.067	6	0.147	6
Satisfaction	0.251	5	0.089	7

There are more problem groups available in the model with the satisfied p values using the all possible combinations method than that using the critical ratio (CR) method. There are more p values in the all possible combination method that are higher than those of the critical methods. The p values of critical methods for Schedule and Satisfaction are higher than those of combination method. But the number of remaining problem groups in the model using the critical ratio (CR) method is smaller than those of combination method. Schedule and Satisfaction have five problem groups for each using the critical ratio (CR) method and have

seven problem groups for each using the all combination method. Although the total number of tested models using the all combination method would be larger than those for the critical ratio (CR) method where there are less problem group combinations per model, it clearly shows that all combination is preferred to find the best-fitted model with a higher number of problem groups in the model. The revised concept of critical ratio (CR) method may not work effectively in this model trimming process.

To finalize the model for each success parameter, the selection priority will go to the highest p value with the largest number of problem groups in the model. There is no issue on selection of best-fitted model for Cost, Quality, and Safety. All combination models satisfy the highest p value and the largest number of problem groups. So three models from all combination method will be chosen as the best-fitted model for Cost, Quality, and Safety. On the other hand, there may be some issues with Schedule and Satisfaction. The p values of both success parameters of the critical ratio (CR) method are higher than those of all combination method but fewer number of problem groups than those of all combination. Which model has to be chosen? Recalling why all this modeling process is needed for the first time. The initial original eight-problem group model has rejected the null hypothesis. If any project success parameter is not manifested by the eight problem groups, then how many possible problem groups can manifest the project success parameter? If there is any model that meets the minimum p value with a larger number of problem groups, then that model will have to be selected for the best-fitted model. So the model of Schedule and Satisfaction from the all combinations method has to be chosen to be the best-fitted model. If the all combinations method had been performed first for Schedule and Satisfaction, the model trimming process using the critical ratio (CR) method would not have been necessary because there is a model that meets the p value with seven

problem groups for Schedule and Satisfaction. Finally the best-fitted model for each success parameter is the model from all combination method.

Final goodness-of-fit test indices

Thus far, only the p value has been used for the selection of the best-fitted model for each success parameter, however, it is necessary and recommended that other indices be reviewed as well (Brown 2006). There are three categories and four different types of goodness-of-fit test indices available besides the p value. The three categories are Absolute Fit, Parsimony Correction, and Comparative Fit. The four types of indices are Standardized Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). Table 4-28 shows the summary of these indices of the final CFA model for each success parameter.

Table 4-28. Summary of goodness-of-fit indices

Category	Index	Cutoff Value[1]	Success Parameter				
			Cost	Schedule	Quality	Safety	Satisfaction
χ^2	H_0: $\Sigma = S$ H_a: $\Sigma \neq S$ or no restriction Should fail to reject H_0 at α = 0.05	> 0.05	0.189	0.188	0.129	0.147	0.089
Absolute Fit	Standardized Root Mean Square Residual (SRMR)	< 0.08	0.039	0.065	0.034	0.032	0.062
Parsimony Correction	Root Mean Square Error of Approximation (RMSEA)	< 0.10	0.056	0.056	0.066	0.070	0.074
Comparative Fit	Comparative Fit Index (CFI)	> 0.95	0.856	0.881	0.980	0.986	0.832
	Tucker-Lewis Index (TLI)	> 0.95	0.904	0.921	0.987	0.991	0.888

Notes: 1. Source: Brown 2006

All indices satisfy the cutoff values except for comparative fit. The values of Quality and Safety satisfy the comparative fit but the rest of the project success parameters do not meet the cutoff values that are greater than 0.95 for both indices. The index values of Cost and Schedule are close to the cutoff value and that of Satisfaction is a little bit further away than the other two success parameters. The two indices values of the comparative fit of Satisfaction will be increased to 0.919 and 0.951 for CFI and TLI respectively if the model has six problem groups without AL and CA in the model. In this case the model fit is increased to satisfy one of two indices but there are only six problem groups not seven. The fewer number of problem groups, the better model fit is. But for this research, even though a good model fit is important, the number of problem groups in the model explained by CFA is important as well. So the current selected model for each success parameter is good enough for the goodness-of-fit tests even though some of them do not satisfy the comparative fit by itself.

Parameter Estimate and Significance

The process of the computation of parameter estimate is already addressed in the previous section. In this section, there are two main topics presented. One is the parameter estimate (factor loading) and its statistical significance. Based on the best-fitted model for each success parameter, the parameter estimate is performed. The raw estimate is computed and then the raw estimate will be converted into the standard estimate. In this process, the significance of the parameter has to be checked. To be statistically significant, the critical ratio (CR) value has to be greater than 1.96 at $\alpha = 0.05$. All the raw estimates of each project success parameter using different bases are shown in Appendix E. It also includes unique variances for each success parameter. Even though the raw estimate is different from the base problem group, the standard estimate and the unique variances are not. All the raw estimates using different bases and unique

variances are statistically significant at $\alpha = 0.05$ which means the critical ratio values are greater than 1.96. Table 4-29 shows the summary of the standard estimate (factor loading) for each success parameter.

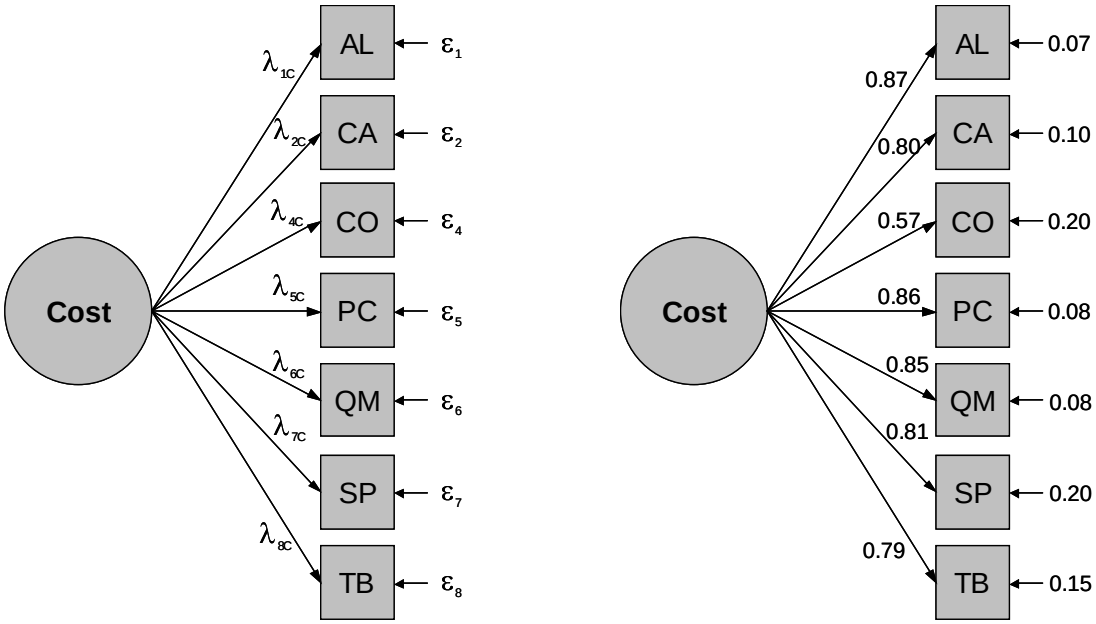
Table 4-29. Summary of standard estimate (factor loading)

Problem Groups	Success Parameters				
	Cost	Schedule	Quality	Safety	Satisfaction
AL	0.867	0.865	0.903		
CA	0.804	0.498	0.670	0.848	0.938
CM		0.813	0.835	0.877	0.931
CO	0.574	0.726	0.707	0.821	0.870
PC	0.859	0.746		0.948	0.939
QM	0.846	0.846	0.616	0.919	0.860
SP	0.806		0.799	0.504	0.865
TB	0.788	0.846	0.898		0.776

From the model trimming process, the number of problem groups per success parameter has been set up. Cost, Schedule, Quality, and Satisfaction have seven problem groups and Safety has only six problem groups as shown in Table 4-29 and also one of the graphical path diagrams with denotations and output results as example for Cost is shown in Figure 4-5. The path diagrams shown in Figure 4-5 are based on the latent factor (Cost).

All the values in both figures are rounded up to two decimal places for convenience. All the denotations in plot A of Figure 4-5 are the counterpart of values for factor loadings and unique variances in plot B of Figure 4-5. Each problem group consists of a factor loading and a unique variance. The unique variance for Cost is available in Appendix E as mentioned early. The path diagram can be presented by equation shown in Table 4-30.

The equations are based on each individual problem group and are in the form of a regression model. The largest slope is from AL with 0.87 and the smallest slope is from CO with 0.57. Although the interpretation of factor loading varies among researchers (Thompson 2004), these factor loadings are regression slopes between a latent factor and indicator variables (Brown 2006; Garson 2008c). A latent factor is a project success parameter and indicator variables are



A) Denotations B) Outputs

Figure 4-5. Path diagram.

Table 4-30. Equation forms for cost

Denotation	Real Output
$AL = \lambda_{1C}\eta_C + \varepsilon_1$	$AL = 0.87\eta_C + 0.07$
$CA = \lambda_{2C}\eta_C + \varepsilon_2$	$CA = 0.80\eta_C + 0.10$
$CO = \lambda_{4C}\eta_C + \varepsilon_4$.	$CO = 0.57\eta_C + 0.20$
$QM = \lambda_{5C}\eta_C + \varepsilon_5$	$QM = 0.86\eta_C + 0.08$
$PC = \lambda_{6C}\eta_C + \varepsilon_6$	$PC = 0.85\eta_C + 0.08$
$SP = \lambda_{7C}\eta_C + \varepsilon_7$	$SP = 0.81\eta_C + 0.20$
$TB = \lambda_{8C}\eta_C + \varepsilon_8$.	$TB = 0.79\eta_C + 0.15$

project problem groups in this research. These regression slopes can be interpreted as the impact on a latent factor (Bassioni et al. 2008; Eskildsen et al. 2001). The raw data shows the evaluations of the problems' that negatively impact on each success parameter. From this perspective, the factor loadings shown in Table 4-29 are negative impacts on each project success parameter. The highest value means the highest negative impact on any success

parameter and the lowest value means the lowest impact on any success parameter. Most of problem groups have different impacts on each project success parameter. It supports one of the hypotheses of this research, that "each problem group will have a different impact on each success parameter."

The CFA model procedures for this research have been addressed. The five initial CFA models, from the 100 point data set, have eight problem groups to be tested whether they are manifested by all eight problem groups or not. At the end of the process, none of them are manifested by eight problem groups but it is found that each project success parameter is manifested by six or seven problem groups. The impacts of problems on each project success parameter are different from each other. Most of problem groups dynamically and differently response to each project success parameter. This information on the number of problem groups within each project success parameter and impacts of the problem groups on success parameters will be useful and can be a good guideline for further studies on the multiple project success parameters. The next chapter will be discussed how this information can be used for developing a tool for potential project problem identification.

CHAPTER 5
APPLICATION OF CFA MODEL OUTPUTS

Background

In the preceding chapter, the relationship between certain project success parameters and some problem groups has been discussed. Each problem group has a different impact on a project success parameter. It is clear and easy to manage or focus on which problem group has the most negative impact when there is only one project success parameter. In the reality, there are more than one project success parameters. The two most common project success parameters are cost and schedule. A project is considered as successful when it is completed under budget and within schedule. So there are many articles available on these two project success parameters such as index modeling (Gibson and Dumont 1995); performance measure and project outcome forecasting (Choi et al. 2006; Russell et al. 1996). These studies focused on cost and schedule. As society changes rapidly, the demands on the construction industry are not focusing on only cost and schedule any more. There are additional success parameters other than cost and schedule such as quality and safety. Even though Choi et al (2006) addresses multiple project success parameters and project outcome forecasting, it mainly discusses each individual success parameter. It does not see the multiple project success parameters as one whole project success when a project has more than two success parameters with a different weight on each success parameter. Griffith et al (1999) shows how project success index could be computed and changed depending upon the criteria and their weights. If there are multiple project success parameters available with different weight priorities for a project, then how can this project be controlled? When the project has its own potential problems, which problems should be considered as the most serious or critical for the project success? Using outputs of the previous

chapter and the SMART*S* technique, this chapter will show the process involved in coming up with the answer those questions.

Single Multi-Attribute Rating Technique Using Swing Weight (SMART*S*)

Overview

In Chapter 2, the basic procedure of SMART*S* has been discussed. This method is helpful to narrow down the options based on the evaluation of options related to attributes as discussed in Chapter 2. Attributes would be project success parameters and options would be eight project problem groups for this research. To use this technique, there are two concerns about the independence properties of the measurement attributes. One is the value independence and the other is defined as environmental independence (Edwards 1977; Oyetunji 2001). Another concern with the values is the dominance among options (Edwards and Barron 1994; Winterfeldt and Edwards 1986). Any option dominating others should be eliminated. All of the input values should meet these criteria to use this technique. In this section, the computation of input values, independence properties, dominance option, and tool development and its validation process will be discussed.

Computation of Input Values

To perform SMART*S*, there needs to be a set of input values for multi-attributes (project success parameters) and their options (problem groups). In the preceding chapter, the relationships between project success parameters and eight problem groups is defined as shown in Table 4-29. The values shown in Table 4-29 consider the impact of each problem group on each success parameter. The higher the values, the more negative the impact on a project success parameter. So the values in Table 4-29 are good enough as input values for SMART*S*. The raw values are showing as values with three decimal places so they have to be converted into whole numbers for the convenience of further work in this process. There are two

approaches to convert the raw values into whole numbers. One approach is a value of option A over a value of option B when the value of option B is the highest value among options and the other value is a value of option A over a value of option B when the value of option B is the sum of all options. The first approach is the computation of a relative ratio between a value and the highest value among values (Oyetunji 2001). Obviously the highest value would be 100 and others will be less than 100 if 100 is set to be the highest value. The second approach is the computation of the proportional ratio between a value of an option and the sum of all options (Bassioni et al. 2008; Eskildsen et al. 2001). The first approach is useful when all attributes have the same highest values. The second approach is useful when all attributes have different highest values. The same input values of the first approach will come out if the input values of second approach are computed as the first one. So there is no big difference in the input value computations. For this study, the second approach is chosen for the conversion of raw data into whole numbers and the computation example of Cost from Table 4-29 shown in Table 5-1.

Table 5-1. Conversion factor loadings for cost

Problem Group	Factor Loading	Proportional Ratio		Final Impact
AL	0.867	0.867/5.544 =	0.156	156
CA	0.804	0.804/5.544 =	0.145	145
CO	0.574	0.574/5.544 =	0.104	104
PC	0.859	0.859/5.544 =	0.155	155
QM	0.846	0.846/5.544 =	0.153	153
SP	0.806	0.806/5.544 =	0.145	145
TB	0.788	0.788/5.544 =	0.142	142
Total	5.544		1.000	1,000

There are seven problem groups available for Cost and CM is excluded. The total sum of factor loading in Table 5-1 is 5.544. Each factor loading for AL, CA, CO, PC, QM, SP, and TB is 0.867, 0.804, 0.574, 0.859, 0.846, 0.806, and 0.788 respectively. The proportional ratio for AL is 0.867/5.544 = 0.156. The final impact values are multiplied by 1,000 since it is easier to use 156 than 0.156 (Bassioni et al. 2008; Eskildsen et al. 2001). The highest conversion value is

156 from AL and the lowest conversion value is 104 from CO. The index value of 156 stands for the maximum negative impact on Cost from AL and the index value 104 stands for the maximum negative impact on Cost from CO. The sum of converted values of problem groups on each project success parameter will be 1,000. It means that the index value of maximum negative impact on each success parameter is 1,000. Using this method, all the raw values of factor loadings in Table 4-29 are converted into the whole number values as shown in Table 5-2

Table 5-2. Summary of conversion values for all success parameters

Problem Groups	Success Parameters				
	Cost	Schedule	Quality	Safety	Satisfaction
AL	156	162	166		
CA	145	93	123	172	152
CM		152	154	178	151
CO	104	136	130	167	141
PC	155	140		193	152
QM	153	158	113	187	139
SP	145		147	103	140
TB	142	158	165		126
Sum	1,000	1,000	1,000	1,000	1,000

The conversion numbers shown in the table 5-2 is the final input for SMART*S*. The sum of each project success parameter is 1,000 and each success parameter has its highs and lows for the maximum impacts on a given success parameter. Next, these conversion values will be checked to determine whether they satisfy the independence properties and dominance of the options.

Independency Properties of Values

As mentioned early, there are two types of checks to be performed to determine the independency properties of the values (Edwards 1977; Oyetunji 2001). One is the value independence and the other is defined as environmental independence. The aggregation rule on the SMART*S* process is based on the assumptions of independence of the measurement attributes considered in a selection analysis (Oyetunji 2001). Regarding value independence, Oyetunji

(2001) addresses "value independency, which applies essentially to objective measurement attributes that are assessed in natural units." As shown in Table 4-29, the values of factor loadings are showing relationships between success parameters and the problem groups. The values in Table 4-29 show that there is no relationship between problem groups. Due to the relationship between success parameters and problem groups, each problem group is naturally independent from each other. It means that they satisfy the value independency. For the convenience of the application, all input values are computed into scales out of 1,000. Edwards (1977) defines the value independence means that the extent of an impact for problem A over B of a success parameter is unaffected by the position of the entity being evaluated on other success parameters. The final conversion values satisfy the value independency because all factor loadings are converted into maximum impact using the proportional ratio on success parameters. A conversion value is an impact for problem group over the overall impacts. This meets the definition of the value independency as well.

The other aspect of the independence properties is environmental independence. The environmental independence indicates the lack of correlation between the levels of problem groups with respect to two project success parameters (Oyetunji 2001). For example the values of Cost and Schedule are compared to problem group by problem group. If the ways the values exist by problem groups are similar, then the correlation between Cost and Schedule will be high. If the pattern of values by problem groups is the same to both, the correlation will be 1.0. In this case, a perfect correlation is a violation of the environmental independence and it can lead to double counting (Edwards 1977). Due to this double counting, if two project parameters are perfectly environmentally correlated, only one of them need be included in the evaluation

process (Edwards 1977). Edwards (1977) also indicates that the acceptable range or cutoff value of correlations with respect to the environmental independence has not been determined yet.

There are three approaches to determine the environmental independence among project success parameters. One approach is to compare values of a pair of success parameters (Oyetunji 2001). Another is to compute correlations between success parameters. And the third approach is to plot the values of a pair success parameters (Oyetunji 2001). The first one is easy to define the environmental independence. If a pair of success parameters has the same value pattern and the same value by problem group, which is a perfect correlation, the value will be zero when the subtraction is done between them. There are 10 pair combinations of project success parameters among five project success parameters. A pair from Cost and Schedule and its value difference is shown in Table 5-3 as example.

Table 5-3. Value difference between two parameters

Problem Group	Success Parameter		Value Difference (Cost – Schedule)
	Cost	Schedule	
AL	156	162	(6)
CA	145	93	52
CM	0	152	(152)
CO	104	136	(32)
PC	155	140	15
QM	153	158	(6)
SP	145	0	145
TB	142	158	(16)

Table 5-3 clearly shows that there is no pattern in between two project success parameters with respect to the problem groups. All the negative values are in the parenthesis. The output of rest of the nine pair combinations of two project success parameters among five project success parameters are shown in Table 5-4. Similar to the pair of Cost and Schedule, the rest of pairs have no pattern in the value difference with respect to problem groups. Each pair of parameters shows the irregular pattern in value difference. These outputs show that there are no high environmental correlations between project success parameters in the selection process.

Table 5-4. Value difference between two project success parameters*

Problem Group	Value Difference								
	Cos - Qua	Cos- Saf	Cos - Sat	Sch - Qua	Sch - Saf	Sch - Sat	Qua - Saf	Qua - Sat	Saf - Sat
AL	(10)	156	156	(4)	162	162	166	166	0
CA	22	(27)	(7)	(30)	(79)	(59)	(49)	(28)	21
CM	(154)	(178)	(151)	(2)	(26)	2	(25)	3	28
CO	(27)	(63)	(37)	6	(31)	(5)	(37)	(11)	26
PC	155	(38)	3	140	(53)	(12)	(193)	(152)	41
QM	39	(34)	13	45	(28)	19	(73)	(26)	48
SP	(2)	43	5	(147)	(103)	(140)	45	7	(37)
TB	(23)	142	17	(7)	158	33	165	40	(126)

* Cos (Cost), Sch (Schedule), Qua (Quality), Saf (Safety), and Sat (Satisfaction)

The second one is to compute the correlations between project success parameters. Table 5-5 shows the correlations between project success parameters using SPSS.

Table 5-5. Correlations between project success parameters

	Cost	Schedule	Quality	Safety	Satisfaction
Cost	1.000				
Schedule	(0.181)	1.000			
Quality	(0.266)	(0.059)	1.000		
Safety	(0.308)	(0.079)	(0.588)	1.000	
Satisfaction	(0.284)	(0.282)	(0.390)	0.721	1.000

The negative correlations In Table 5-5 are presented in the parenthesis. All correlations are negative except for the pair for Safety and Satisfaction. The correlation between Safety and Satisfaction has the highest correlation at 0.721 and the correlation between Schedule and Quality has the lowest correlation at 0.059. Except for the correlation of Satisfaction and Safety, all correlations are less than 0.6. According to the range of correlation by Olson (1987), the correlation between Safety and Satisfaction is moderately correlated and the rest of correlations have no relationship. It is evident that that there is no relationship between pairs of project success parameters even though one of the correlation values is moderately correlated.

The last one is to plot the values of a pair of project success parameters with respect to problem groups. If two success parameters are perfectly correlated, all the values will be plotted on the trend line and its variability (R^2) will be 100% (Oyetunji 2001). The total number of pairs

of project success parameters is ten. Each pair of success parameters will be plotted as a $y = ax + b$ relationship. Table 5-6 shows the summary of variability of ten pairs and Figure 5-1 shows the plot of Satisfaction and Safety as example.

Table 5-6. Summary of variability

Variability	Pairs of Success Parameters									
	1	2	3	4	5	6	7	8	9	10
	Cos Sch	Cos Qua	Cos Saf	Cos Sat	Sch Qua	Sch Saf	Sch Sat	Qua Saf	Qua Sat	Saf Sat
R^2 (%)	3.29	7.09	9.48	8.05	0.34	0.63	7.95	34.52	15.20	52.03

where Cos (Cost), Sch (Schedule), Qua (Quality), Saf (Safety), and Sat (Satisfaction)

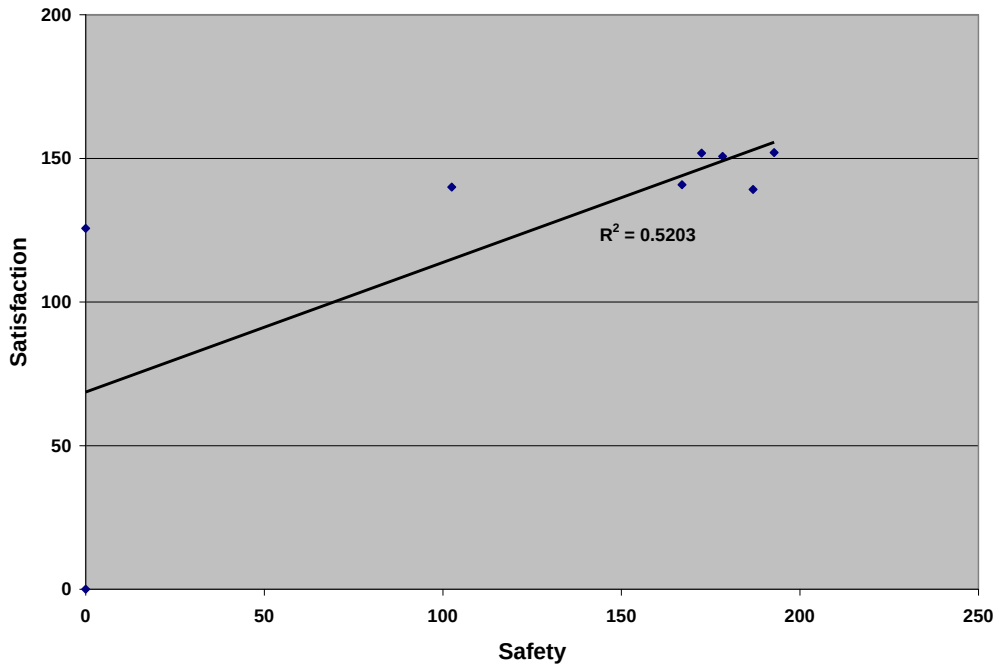


Figure 5-1. The plot of safety vs. satisfaction

Pair 10 comprised of Safety and Satisfaction in Table 5-6 has the highest variability among pairs with 52.03% and its plot is shown in Figure 5-1. All the values of Safety are plotted on the x-axis and all the values of Satisfaction are plotted on the y-axis. After plotting values of both success parameters, a trend line can be drawn as shown in Figure 5-1. If both success parameters are perfectly correlated, then all the values of both parameters will be on the trend line and the variability of the trend line will be 100%. As shown in Figure 5-1, none of the values is on the

trend line. For the references, all plots with trend lines and variability of the ten pairs are available in Appendix F. The second highest variability is in Pair 8 consisting of Quality and Safety with 34.52%. The third highest variability is 15.20% for Pair 9 consisting of Quality and Satisfaction. The rest of the variabilities are too small to expect the trend and relationship. The maximum variability is 52.03% and the lowest is 0.34% among all ten pairs of variabilities. Even though 52.03% is the highest variability, it is still not statistically enough to explain the relationship between two project success parameters. From this method, there is no significant relationship between all pairs of success parameters. It is clearly evident that all pairs of project success parameters are environmentally independent.

Dominance of Problem Groups

The value independency mainly addresses the value independency between project success parameters. On the other hand, the dominance focuses on the problem groups. Even though the results of the CFA models already show that problem groups respond differently to each project success parameter, the dominance check has to be performed. Problem groups are alternatives showing the degree of being critical to a given set of project success parameters. A problem group is classified as dominant if the problem group is superior to other problem groups with respect to all project success parameters. In this case, the dominant problem group has to be eliminated because the problem group is always out-performed so there is no chance to change in positioning for other problem groups (Edwards 1977; Oyetunji 2001). To satisfy the SMART*S* process, there are no dominant problem groups among problem groups.

The easiest way to check the dominance among problem groups is to check the value difference between two problem groups with respect to five project success parameters (Oyetunji 2001). The possible combination of pairs of problem groups is 28. The order in a pair does not matter here for example AL - CA or CA - AL. If the value difference between two problem

groups is larger than zero or smaller than zero with respect to all five project success parameters, then one of problem groups that have a larger value is the dominant problem group. The out-performed problem group has to be considered for removal from the alternatives because there is no chance to change in positioning with respect to project success parameters. Table 5-7 shows the value difference between two problem groups. All the value differences less than zero are shown in the parenthesis. To avoid the dominance problem group, the value difference of each pair in the row in Table 5-7 has to be a combination of larger and less than zero values. If all the values are larger or smaller than zero, then as stated earlier, one of problem groups will be considered as dominant.

Table 5-7. Value difference between two problem groups

No.	Problem Pairs			Success Parameters				
				Cost	Schedule	Quality	Safety	Satisfaction
1	AL	-	CA	11	69	43	(172)	(152)
2	AL	-	CM	156	10	13	(178)	(151)
3	AL	-	CO	53	26	36	(167)	(141)
4	AL	-	PC	1	22	166	(193)	(152)
5	AL	-	QM	4	4	53	(187)	(139)
6	AL	-	SP	11	162	19	(103)	(140)
7	AL	-	TB	14	4	1	0	(126)
8	CA	-	CM	145	(59)	(30)	(6)	1
9	CA	-	CO	41	(43)	(7)	5	11
10	CA	-	PC	(10)	(46)	123	(20)	0
11	CA	-	QM	(8)	(65)	10	(14)	13
12	CA	-	SP	0	93	(24)	70	12
13	CA	-	TB	3	(65)	(42)	172	26
14	CM	-	CO	(104)	16	24	11	10
15	CM	-	PC	(155)	13	154	(14)	(1)
16	CM	-	QM	(153)	(6)	40	(9)	11
17	CM	-	SP	(145)	152	7	76	11
18	CM	-	TB	(142)	(6)	(12)	178	25
19	CO	-	PC	(62)	(4)	169	(18)	(9)
20	CO	-	QM	(59)	(22)	22	(14)	1
21	CO	-	SP	(50)	136	(22)	45	1
22	CO	-	TB	(46)	(22)	(46)	117	12
23	PC	-	QM	2	(19)	(113)	6	13
24	PC	-	SP	10	140	(147)	90	12
25	PC	-	TB	13	(19)	(165)	193	26
26	QM	-	SP	7	158	(34)	84	(1)
27	QM	-	TB	10	0	(52)	187	14
28	SP	-	TB	3	(158)	(18)	103	14

Every pair of problem groups has its ups (above zero) and downs (below zero) with respect to five project success parameters. It does not look like that there are serious dominant problem groups existing among problem groups. Regarding AL and its pair combinations, due to the highest value among problem groups in three success parameters, AL is out-performed in Cost, Schedule, and Quality but not in Safety and Satisfaction. AL would be removed if it were out-performed in Safety and Satisfaction as well. The value differences in Table 5-7 are plotted into two graphs as shown in Figure 5-2 and 5-3 for visual checking. Figure 5-2 shows the combination No. 1 through 13 and Figure 5-3 shows the rest of combinations.

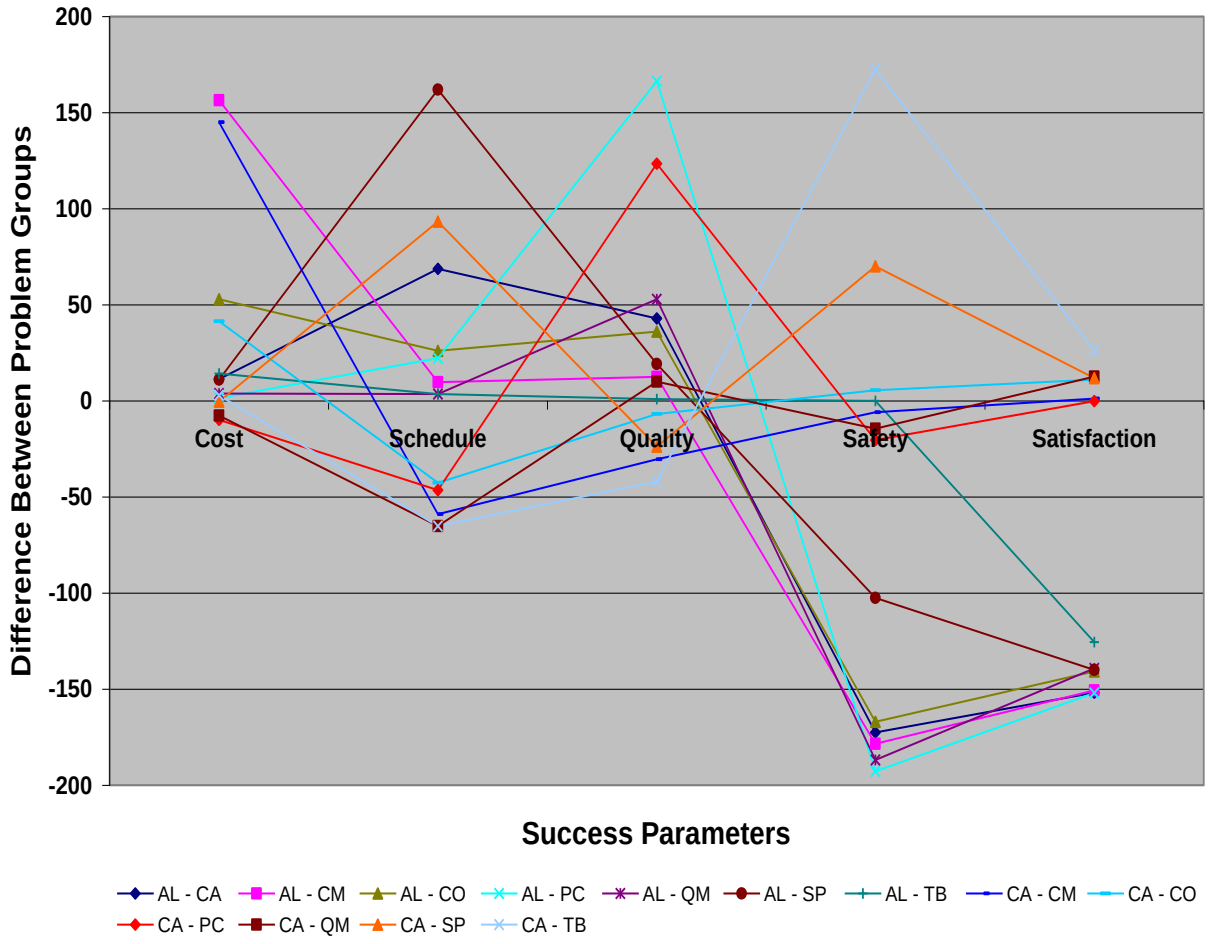


Figure 5-2. Value difference between problem groups part 1

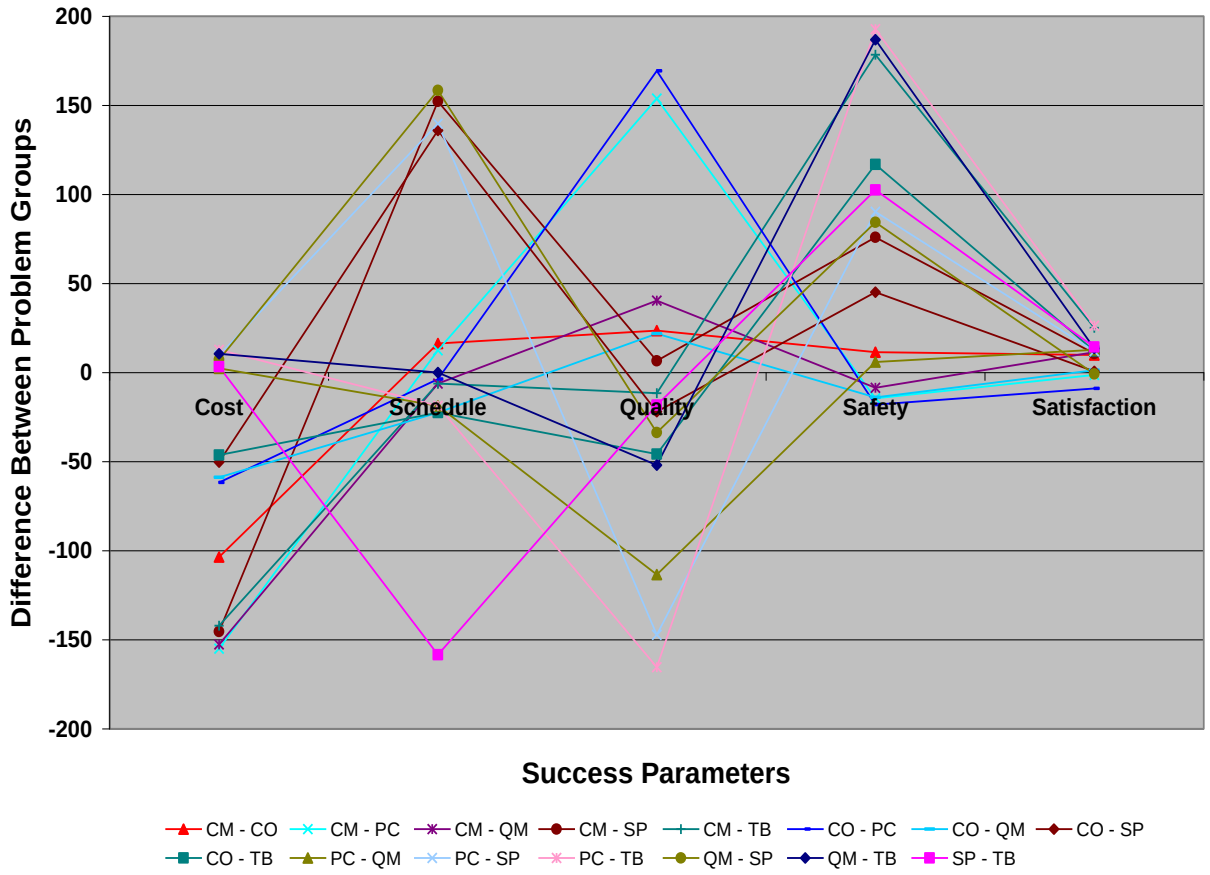


Figure 5-3. Value difference between problem groups part 2

In addition to Table 5-7, visual checking is performed using Figure 5-2 and 5-3. The two graphs support the conclusion there are no dominant problem groups among themselves. All the property for the input values of the SMARTS process has been tested. Those properties are the independency property and dominance of problem groups. The independence property has two categories. One is the value independency and the other is the environmental correlation. The input values for the SMARTS from the CFA models satisfy these properties. The next property checked is the dominance problem groups among themselves. The value difference between two problem groups and visual checking using two plots show that there are no dominant problem groups among themselves. So the final conversion values in Table 5-2 satisfy all the property of the SMARTS process and are ready to be used in tool development.

Basic Concept of Application

Overview

As discussed in the section 2.5 of the Chapter 2, the SMART*S* process shows the best alternative (problem group) based on the preferences or weights of factors (project success parameters) as a form of aggregated scores. The preceding section showed the whole process of testing the property of input values for the SMART*S* process. The input values are the output of CFA models. Each value in the table is the maximum negative impact of the index value on each success parameter. The values are various among problem groups and project success parameters. From this point, there are five project success parameters available with a different weight or preference and there are eight potential problem groups available with maximum impact on each success parameter. Using the SMART*S* process, the degrees of being critical problem groups can be computed by changing the weight or preference of project success parameters. The aggregated scores represent the maximum degree of being critical of a problem group with respect to the preference or weights of project success parameters. The higher the aggregated score of a problem group, the most critical problem group is. The SMART*S* process has only one criterion in this study, which is project success parameter. As stated early, all the values of problem groups are their maximum negative impact on project success parameters. It would be impossible to have all eight-problem groups as the most critical as they are at the same time for a project. There will be certainly a difference in the degrees of severity of the problem groups. So in addition to the project success parameters, it is necessary to add the degree of severity of the problem group into the application development. The final application has two criteria, which are five project success parameters and eight project problem groups. In this section, the process of the computation of aggregated scores using the SMART*S* process and the

degree of severity of problem group to select the most critical problem group will be showed using equations and numerical examples for a given scenario.

Scenario

The following is a scenario on the explanation of the SMARTS process and the degree of severity of the problem for the basic concept of the application. The process will be discussed based on this scenario and the issues related to this study.

A contractor has been awarded a project. The contractor uses a system that classifies the problems it encounters on projects into eight (8) problem groups - AL (alignment), CA (constructability), CM (change management), CO (contracting), PC (project controls), QM (quality), SP (safety practices), and TB (team building). The severity of problems such as how serious or minor they are varies among the problem groups. The owner of the project is very demanding and evaluates their projects based on five different success parameters - cost, schedule, quality, safety, and satisfaction. The contractor wants to know which problems he has to be concerned with the most and the least under any given conditions (severity of the problem and the owner's priorities based on success parameters) to meet the owner's expectation on project.

The issues related to this scenario are:

1) How does the contractor know which of the eight problem groups is the most critical?;

2) How do the problem groups impact each success parameter?;

3) How does the contractor manage the problems to minimize the impacts of problems?; and

4) How do priority weights of the success parameters affect the impacts of problems?

Equation Example

Denotation of input table

From the CFA models, there are maximum impacts of problem groups on each success parameter. All the impacts of each problem group are denoted as shown in Table 5-8.

Table 5-8. Impacts of problems on each success parameter

Problem Group	Cost	Schedule	Quality	Safety	Satisfaction	Total
AL	COS_{AL}	SCH_{AL}	QUA_{AL}	SAF_{AL}	SAT_{AL}	AL_{TOTAL}
CA	COS_{CA}	SCH_{CA}	QUA_{CA}	SAF_{CA}	SAT_{CA}	CA_{TOTAL}
CM	COS_{CM}	SCH_{CM}	QUA_{CM}	SAF_{CM}	SAT_{CM}	CM_{TOTAL}
CO	COS_{CO}	SCH_{CO}	QUA_{CO}	SAF_{CO}	SAT_{CO}	CO_{TOTAL}
PC	COS_{PC}	SCH_{PC}	QUA_{PC}	SAF_{PC}	SAT_{PC}	PC_{TOTAL}
QM	COS_{QM}	SCH_{QM}	QUA_{QM}	SAF_{QM}	SAT_{QM}	QM_{TOTAL}
SP	COS_{SP}	SCH_{SP}	QUA_{SP}	SAF_{SP}	SAT_{SP}	SP_{TOTAL}
TB	COS_{TB}	SCH_{TB}	QUA_{TB}	SAF_{TB}	SAT_{TB}	TB_{TOTAL}

The total impacts of each problem group on success parameters are shown in Table 5-8. The weight (priority) of each success parameter is denoted as W_{COS}, W_{SCH}, W_{QUA}, W_{SAF}, and W_{SAT} for cost, schedule, quality, safety, and satisfaction respectively. The success of the project is the combination of each weight of success parameter and the maximum sum of these weights is equal to 5 or the weight would be the proportional ratio (%) of the total sum of weight. Five (5) are chosen for this example. The success of project is expressed as:

$$\text{Success} = W_{COS} + W_{SCH} + W_{QUA} + W_{SAF} + W_{SAT}$$

where, W_{COS}, W_{SCH}, W_{QUA}, W_{SAF}, and/or $W_{SAT} \geq 0$.

Weighted problem group

The weight of each success parameter is defined, and then the weighted total of the problem group is calculated as follows:

$$W_{ALTOTAL} = W_{COS} \times COS_{AL} + W_{SCH} \times SCH_{AL} + W_{QUA} \times QUA_{AL} + W_{SAF} \times SAF_{AL} + W_{SAT} \times SAT_{AL}$$

$$W_{CATOTAL} = W_{COS} \times COS_{CA} + W_{SCH} \times SCH_{CA} + W_{QUA} \times QUA_{CA} + W_{SAF} \times SAF_{CA} + W_{SAT} \times SAT_{CA}$$

$$W_{CMTOTAL} = W_{COS} \times COS_{CM} + W_{SCH} \times SCH_{CM} + W_{QUA} \times QUA_{CM} + W_{SAF} \times SAF_{CM} + W_{SAT} \times SAT_{CM}$$

$$W_{COTOTAL} = W_{COS} \times COS_{CO} + W_{SCH} \times SCH_{CO} + W_{QUA} \times QUA_{CO} + W_{SAF} \times SAF_{CO} + W_{SAT} \times SAT_{CO}$$

$$W_{PCTOTAL} = W_{COS} \times COS_{PC} + W_{SCH} \times SCH_{PC} + W_{QUA} \times QUA_{PC} + W_{SAF} \times SAF_{PC} + W_{SAT} \times SAT_{PC}$$

$$W_{QMTOTAL} = W_{COS} \times COS_{QM} + W_{SCH} \times SCH_{QM} + W_{QUA} \times QUA_{QM} + W_{SAF} \times SAF_{QM} + W_{SAT} \times SAT_{QM}$$

$$W_{SPTOTAL} = W_{COS} \times COS_{SP} + W_{SCH} \times SCH_{SP} + W_{QUA} \times QUA_{SP} + W_{SAF} \times SAF_{SP} + W_{SAT} \times SAT_{SP}$$

$$W_{TBTOTAL} = W_{COS} \times COS_{TB} + W_{SCH} \times SCH_{TB} + W_{QUA} \times QUA_{TB} + W_{SAF} \times SAF_{TB} + W_{SAT} \times SAT_{TB}$$

The original total sum of each problem and its success parameters is based on equal weight among success parameters. That is why each success was assigned a weight of 1 and the sum of weights is 5. If the total sum of the success parameters is less than 5, then it will be adjusted to equal to the number of success parameters.

Degrees of problem severities

The range of degrees of severity of problems is from 0% to 100%. A 0% value means that there are no problems and a 100% value indicates that very serious problems exist. The degree of severity of each problem group is denoted as D_{AL}, D_{CA}, D_{CM}, D_{CO}, D_{PC}, D_{QM}, D_{SP}, and D_{TB}. Using the degree of problems, the final impact of AL as an example can be computed as follows:

$$AL = D_{AL} \times W_{ALTOTAL}$$

$$= D_{AL} \times W_{COS} \times COS_{AL} + D_{AL} \times W_{SCH} \times SCH_{AL} + D_{AL} \times W_{QUA} \times QUA_{AL} + D_{AL} \times W_{SAF} \times SAF_{AL} + D_{AL} \times W_{SAT} \times SAT_{AL}$$

$$= D_{AL} \times (W_{COS} \times COS_{AL} + W_{SCH} \times SCH_{AL} + W_{QUA} \times QUA_{AL} + W_{SAF} \times SAF_{AL} + D_{AL} \times W_{SAT} \times SAT_{AL})$$

Numeric Example

Using equal success priority weights

The conversion values shown in Table 5-2 are based on the equal weight of each success parameter. The sum of each success parameter is equal to 1,000. Table 5-2 can be revised as shown in Table 5-9, which includes the column of the degree of severity, total, and rank and the row of weights. The impacts shown in Table 5-9 are the maximum impacts of the problem groups on each success parameter. Table 5-9 is similar to Table 5-8 except for the weights success parameters. The index values of the column labeled "Total" are the maximum impact of each problem and the sum of the weights for each success parameter. The range of degrees of problems severities is from 0% to 100%. A 0% value means that there are no problems and a 100% value indicates that the most serious problems exist. The values of the column labeled

Table 5-9. Initial impacts with equal weights of 1

Problem Group	Degrees of Problem Group Severity	Success Parameters (Equal Priority Weights=1)						Ranking
		Cost	Schedule	Quality	Safety	Satisfaction	Total	
		1	1	1	1	1	5	
AL	100%	156	162	166			485	8
CA	100%	145	93	123	172	152	686	2
CM	100%		152	154	178	151	635	5
CO	100%	104	136	130	167	141	678	3
PC	100%	155	140		193	152	639	4
QM	100%	153	158	113	187	139	751	1
SP	100%	145		147	103	140	535	7
TB	100%	142	158	165		126	592	6
Total		1,000	1,000	1,000	1,000	1,000	5,000	

"Degrees of Severity" are 100% for all problem groups because all index values in Table 5-9 are their maximum impacts on each success parameter. In the case of impacts, the higher its value the more critical it is. The weight of each success parameter in Table 5-9 is equal to 1 because they are all equally important in this example. With respect to the equal weights among success parameters in this example, the highest impact on project success is for the QM group with an index value of 751 and the lowest impact on project success is AL with an index value of 485. It indicates that a contractor has to be concerned about the QM group the most and the AL group the least if a contractor has a project which has five equally weighted success parameters.

Using unequal success priority weights

In the preceding section success parameters of equal weights (1.0) were addressed. Next success parameters with unequal priority weights will be discussed. For example, a contractor has a project for which five success parameters are used to measure the project success. The owner of project wants a project within budget and schedule. On the other hand, the owners do not care about Safety and Satisfaction as much as they do about Cost and Schedule. Safety is the owners' least concern as a success parameter. Quality is somewhere in the middle range of success parameter. In this case, the two highest priorities for the project are Cost and Schedule and the lowest priority is Safety among five success parameters. These priorities are converted into weights such as 1.3, 1.1, 1.0, 0.9, and 0.7 for Schedule, Cost, Quality, Satisfaction, and Safety respectively. The sum total of the success parameters remains equal to 5. Schedule is the highest priority with a weight of 1.3 and Safety is the lowest priority with a weight of 0.7. Table 5-10 shows the different weights among success parameters and the change in ranking based upon the different weights. For the selected of priority weights, the QM group has the highest impact on the project with an index value of 743 and the SP group has the least impact on project with an index value of 505. It shows that the contractor has to be concerned with QM the most

Table 5-10. Weighted impacts of success parameters

Problem Group	Degrees of Problem Group Severity	Success Parameters (Unequal Priority Weights)						Ranking
		Cost	Schedule	Quality	Safety	Satisfaction	Total	
		1.1	1.3	1.0	0.7	0.9	5	
AL	100%	172	211	166	0	0	549	7
CA	100%	160	121	123	121	137	662	3
CM	100%	0	198	154	125	136	612	6
CO	100%	114	177	130	117	127	664	2
PC	100%	170	182	0	135	137	624	5
QM	100%	168	206	113	131	125	743	1
SP	100%	160	0	147	72	126	505	8
TB	100%	156	206	165	0	113	641	4
Total		1,100	1,300	1,000	700	900	5,000	

and SP the least to meet owner's demand for project success. For the maximum impacts of each problem group (100% Severity) and the unequal weights of the success parameter, the rankings in Table 5-10 are different from that in Table 5-9. It shows that the weights of success parameter affect the impacts of the problem groups. Using this approach, it is possible for the contractor to predict how the impacts of the problem groups change, depending upon changes in the success parameter's priority. For example, the computation of the impact of the AL problem group is as follows:

$$AL = W_{COS} \times COS_{AL} + W_{SCH} \times SCH_{AL} + W_{QUA} \times QUA_{AL} + W_{SAF} \times SAF_{AL} + W_{SAT} \times SAT_{AL}$$

$$= 1.1 \times 156 + 1.3 \times 162 + 1.0 \times 166 + 0.7 \times 0 + 0.9 \times 0$$

$$= 172 + 211 + 166 + 0 + 0$$

$$= 549$$

Using both unequal success priority weights and degrees of problem severity

It is assumed that the contractor previously mentioned is the same contractor here. The situation he/she has faced regarding the weights of project success parameters is the same as before. The contractor figures out which problem groups he/she has to be concerned with the

most and the least based on the priority weight of success. So far he/she is concerned only with the weights of success parameters but not his/her own potential problems on the project. The contractor checks the degree severity for each of the eight problem groups for the project. The contractor expects to have the two most serious problems with the PC and CA problem groups but he/she does not seem to have serious problems with the CO problem group. The rest of problem groups are somewhere in the middle. If a degree of severity value of 100% indicates maximum impact, while a value of 0% indicates no impact on any success parameters, the contractor's problem groups PC, CA, AL, QM, SP, TB, CM, and CO will be assigned the values of 90%, 85%, 75%, 70%, 70%, 70%, 50%, and 20% respectively. The PC problem group has the highest degree of severity (90%), and the CO group has the lowest degree of severity (20%). Table 5-11 shows the different degrees of problems severities for the same success parameters weights that were used in Table 5-10.

Table 5-11. Weighted impacts of both unequal success parameters and degrees of problem severity

Problem Group	Degrees of Problem Group Severity	Success Parameters (Unequal Priority Weights)						Ranking
		Cost	Schedule	Quality	Safety	Satisfaction	Total	
		1.1	1.3	1.0	0.7	0.9	5	
AL	75%	129	158	125	0	0	412	4
CA	85%	136	103	105	103	116	562	1
CM	50%	0	99	77	62	68	306	7
CO	20%	23	35	26	23	25	133	8
PC	90%	153	163	0	121	123	561	2
QM	70%	118	144	79	92	88	520	5
SP	70%	112	0	103	50	88	353	6
TB	70%	109	144	116	0	79	449	3
Total		780	847	631	452	587	3,297	

With the combination of priority weights and degrees of severity, the CA group has the highest impact on project with an index value of 562 and the PC group follows with an index value of 561. The CO group has the least impact on project with an index value of 133. It

means that the contractor has to monitor the CA and PC groups the most and the CO and CM groups the least to meet owner's demand. The ranking of problems is different from Table 5-9 and 5-10. Table 5-9, 5-10, and 5-11 show how the degrees of problem severities and the weights assigned to the success parameters affect the final impact of each problem group. The computation of AL as an example is as follows:

$$AL = D_{AL} \times W_{COS} \times COS_{AL} + D_{AL} \times W_{SCH} \times SCH_{AL} + D_{AL} \times W_{QUA} \times QUA_{AL} + D_{AL} \times W_{SAF} \times SAF_{AL} + D_{AL} \times W_{SAT} \times SAT_{AL}$$

$$= 75\% \times 1.1 \times 156 + 75\% \times 1.3 \times 162 + 75\% \times 1.0 \times 166 + 75\% \times 0.7 \times 0 + 75\% \times 0.9 \times 0$$

$$= 75\% \times 172 + 75\% \times 211 + 75\% \times 166 + 75\% \times 0 + 75\% \times 0$$

$$= 129 + 158 + 125 + 0 + 0$$

$$= 412$$

Summary

Changes in impacts of problem groups on a project have been discussed so far. During this process, it is possible for the contractor to predict what problem groups will be critical for project success based on the owner's success priority and his/her degree of problems severity. As shown in Table 5-11 using the approach described above the contractor will be able to determine which problem has the most and the least impact on the project success parameters based on the current degree of problems severities and success priority weights. The contractor may utilize the degrees of problems to minimize the impacts on a certain success parameter. If there is a change in the priorities of success parameters during construction, the contractor will be able to determine which problem group he/she has to be more concerned with. Table 5-11 is useful to help both owners and contractors focus on certain potential problem groups in order to satisfy the

success of project. This whole process shows that there is a change in ranking of problem groups between the degree of severity with concerning project success parameters and without concerning project success parameters. Table 5-12 shows the difference in ranking.

Table 5-12. The difference in ranking

Problem Groups	Project Success Parameters			
	Without Concerning		With Concerning	
	Degree of Severity	Ranking	Index Value	Ranking
AL	75%	3	412	4
CA	85%	2	562	1
CM	50%	7	306	7
CO	20%	8	133	8
PC	90%	1	561	2
QM	70%	4	520	5
SP	70%	4	353	6
TB	70%	4	449	3

Without considering the project success parameters, all the degrees of severity of problem groups are quantitative-oriented because there is no consideration of the impact of problem groups on project success parameters. On the other hand, the index values concerned with the project success parameters are qualitative-oriented because all the index values are combination of project success parameters and degrees of severity of problems. This will provide a contractor and/or owner with an in-depth analysis of their potential problems. In this section, all the basic concepts of the application process have been discussed. Based on this process, the application will be developed.

Development of Application

Overview

Reassessment of potential project problems has been addressed in the preceding section. Based on the concept of reassessment, the application is developed for the potential users to aid them in reassessing project problems. The application has to be simple and easy to use. In this section, all the application development is addressed in terms of the software, the contents, the

difference between the basic concepts explained and the application, and finally the validation of application.

Application Software Program

The objective of application development is to have an easy and simple to use software package for the potential users. To keep the application accessible to the largest number of users, it was developed using Microsoft Office Excel 2003.

Application Description

This application is named the Potential Project Problem Identification Tool because the final output shows the degrees of being critical of problem groups based on project success parameters and problems. The tool is available as shown in Object 5-1 below.

Object 5-1. Potential problem identification tool as a Microsoft Excel file (.xls 41kb)

There are four worksheets available in the application file. They are Instruction, Input, Output, Success Parameters, and Problem Group. The Instruction worksheet gives the users general information about the application, the Input worksheet is used to assess the project success parameters and the degrees of severity of problem groups. The output shows a histogram chart as the final results based on the input. The worksheet of Success Parameters and Problem Groups addresses the definition of success parameters and problem groups. In the Instruction worksheet, there are three main subtitles available. The three subtitles are Overview, Project Success Parameters, and Project Problem Severity. In Overview, the overall purposes and the basic concepts of this application are addressed. What the outputs mean addresses as well. In Project Success Parameters worksheet, the instruction of weighing project success parameters is explained with an example. It will be explained more detailed later. Finally, the instruction for the degrees of severity of problem groups is explained with an example in Project

Problem Severity. Figure 5-4 shows a screen capture of the Instruction worksheet for this application.

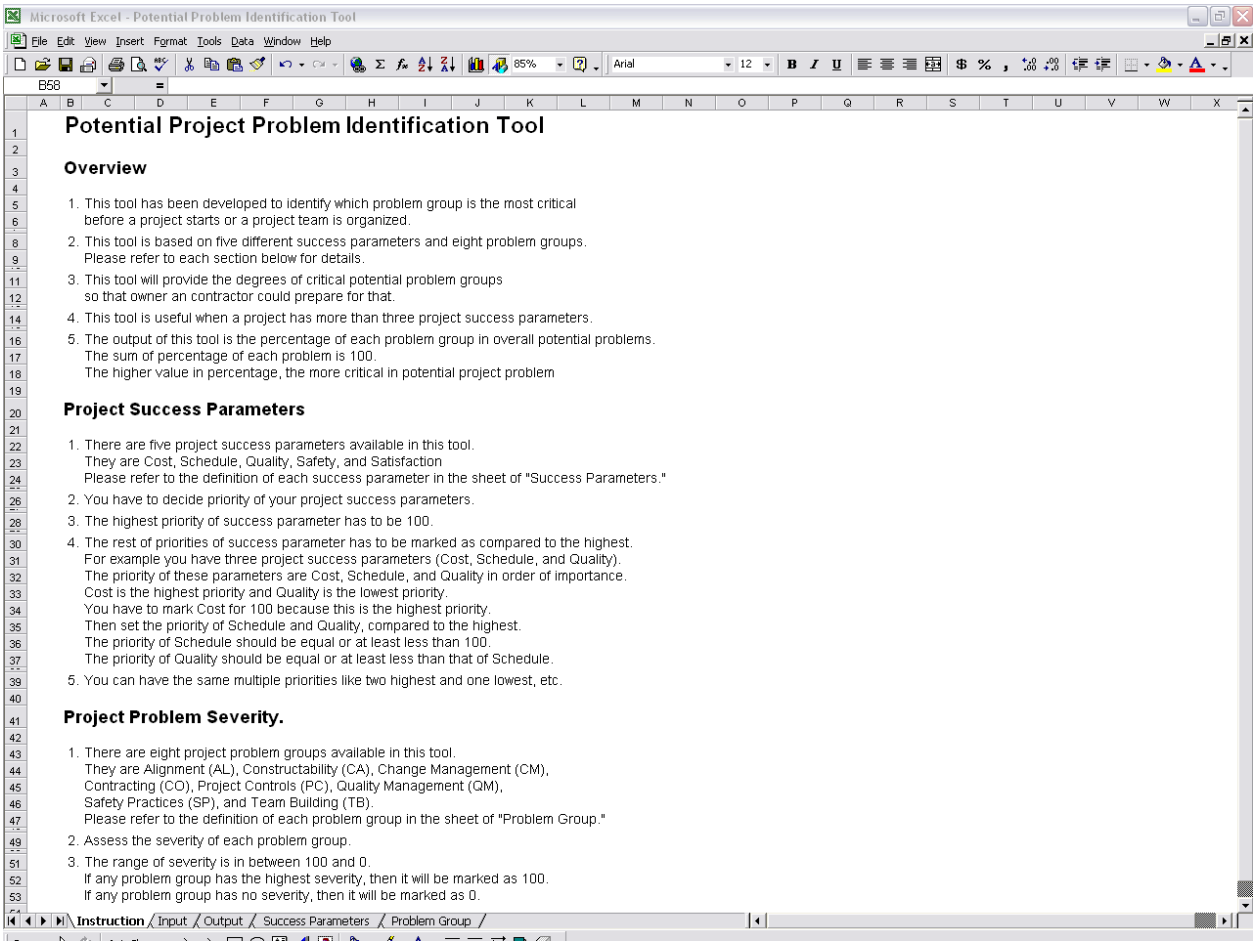


Figure 5-4. Screen capture of Instruction worksheet for application

In the Input worksheet, there are two main activities going on. One is to select the project success parameters with priority weights and the other is to assess project problem groups. As previously stated, there is a difference in weighing the priorities of project success parameters between the application and the original method as described in the preceding sections. The total sum of priority weight is five because each success parameter is equal to one. It will be inconvenient and complicated if this weighing process such as 1.2 or 1.3 is used in the application because there is no limit for the highest weight and also the sum of priority weights has to be five. Setting priority weights and keeping the sum equal to five are not that easy. In

this application, the SMART*S* process is applied to compute the weights using swing weights (Edwards and Barron 1994). Table 5-13 shows the computation of swing weights and its counterpart of the original method. The procedure for computing swing weights is followed;

1. Choose the highest success parameter and its weight should be 100 for this application.
2. Set the priority weights of the rest of project success parameter comparing to the highest one, which is 100 here.
3. Sum all the priority weights of project success parameters
4. Compute the proportional ratio of each priority weight of success parameter over the total sum of project success parameters
5. Apply the computed proportional ratio of priority weight of each success parameter to the calculation of aggregated scores

Table 5-13. Comparisons of original method and swing weights

Success Parameters	Original Method			Swing Weights		
	Weights 1	Weights 2	Proportional Ratio (%)	Weights	Computation	Proportional Ratio (%)
Cost	1.1	.22	22%	85	85/385 = 0.22	22%
Schedule	1.3	.26	26%	100	100/385 = 0.26	26%
Quality	1.0	.20	20%	77	77/385 = 0.20	20%
Safety	0.7	.14	14%	54	54/385 = 0.14	14%
Satisfaction	0.9	.18	18%	69	69/385 = 0.18	18%
Sum	5.0	1.0	100%	385		100%

The proportional ratio will be the same from both methods because the proportional ratio is based on the total sum of weights. If the sum of the priority weights shown in Table 5-11 is set to one, then the weight of each success parameter will be the proportional ratio as shown in Table 5-13. The weights in swing weights in Table 5-13 are the counterpart of those of the original method. In the original method, Schedule is the highest priority with a weight of 1.3. The weight of Cost in the original method can be computed compared to Schedule. The computation of Cost is 1.1/1.3 = 0.85 (85%). The weight of Quality can be computed by 1.0/1.3 = 0.77 (77%). The rest of weights of the success parameters can be computed in the same way. The rest of the computed weights are 0.54 (54%) and 0.69 (69%) for Safety and Satisfaction

respectively. These computed values are shown in the column of Weights in the Swing Weights side in Table 5-13. From the user perspective, swing weights are easy to use in setting the priority weights among success parameters by setting one as the highest value and comparing the rest of the weights to the highest. The original method uses the real priority weight for the computation of aggregated scores. But in the swing weights, the proportional ratio will be used. So the final application will be using the proportional ratio for the calculation of the aggregated scores. This is the main difference between the method in the preceding section and the final application. Figure 5-5 shows the screen capture of the input worksheet.

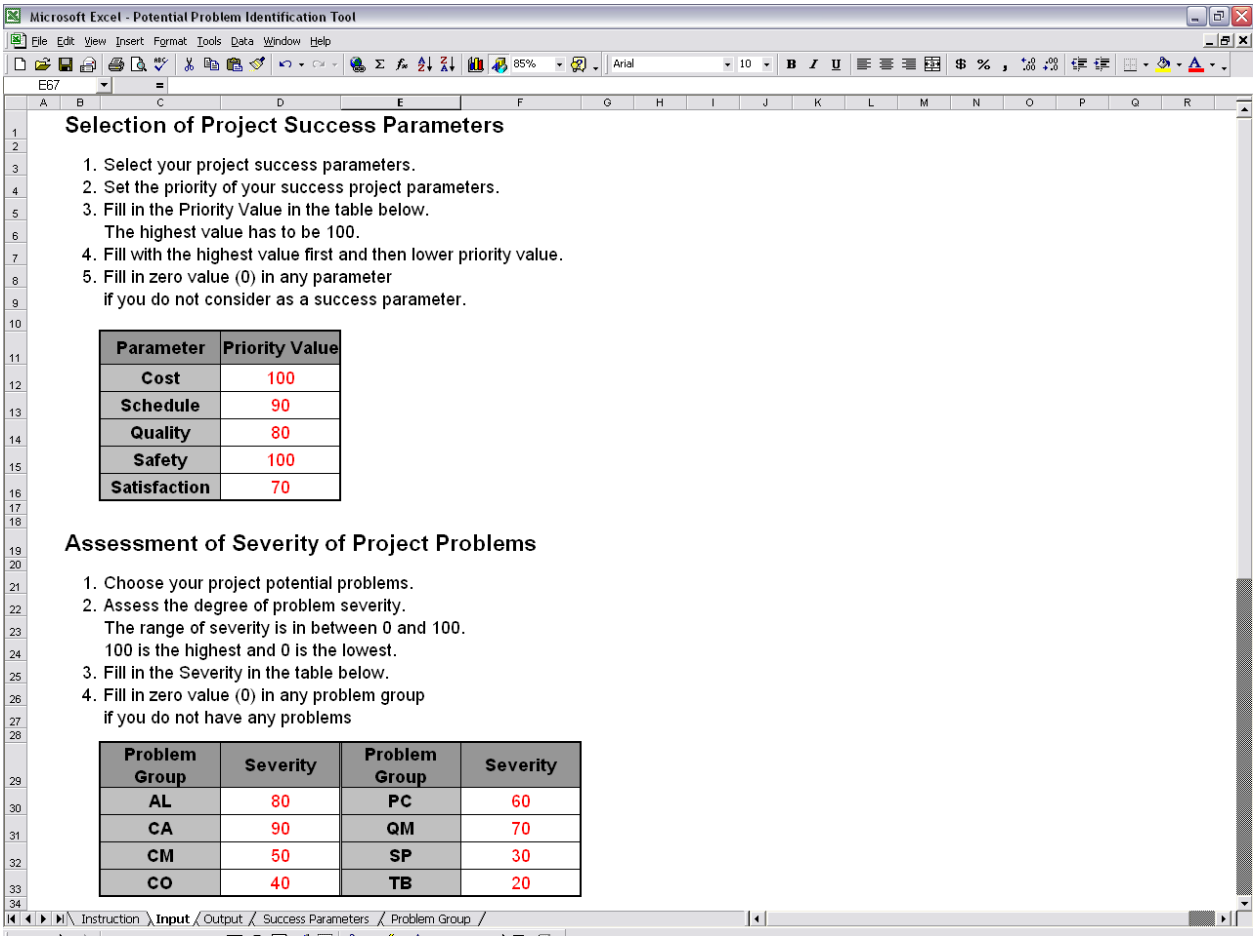


Figure 5-5. Screen capture of input worksheet of application

The assessment of severity of project problems is in the Input worksheet. The range of the degrees of severity is zero (0) through 100. A value of zero means that a project does not have a

problem in a specific problem group and on the other hand, a value of 100 means that a project has a serious problem in that category. So the value of zero (0) that represents no problem is the minimum and the value of 100 that is most serious is the maximum. Based on the assessment of the two categories of project success priority and problem severity, the final output will be shown as a histogram form in the Output worksheet. Figure 5-6 shows the screen capture of the Output worksheet.

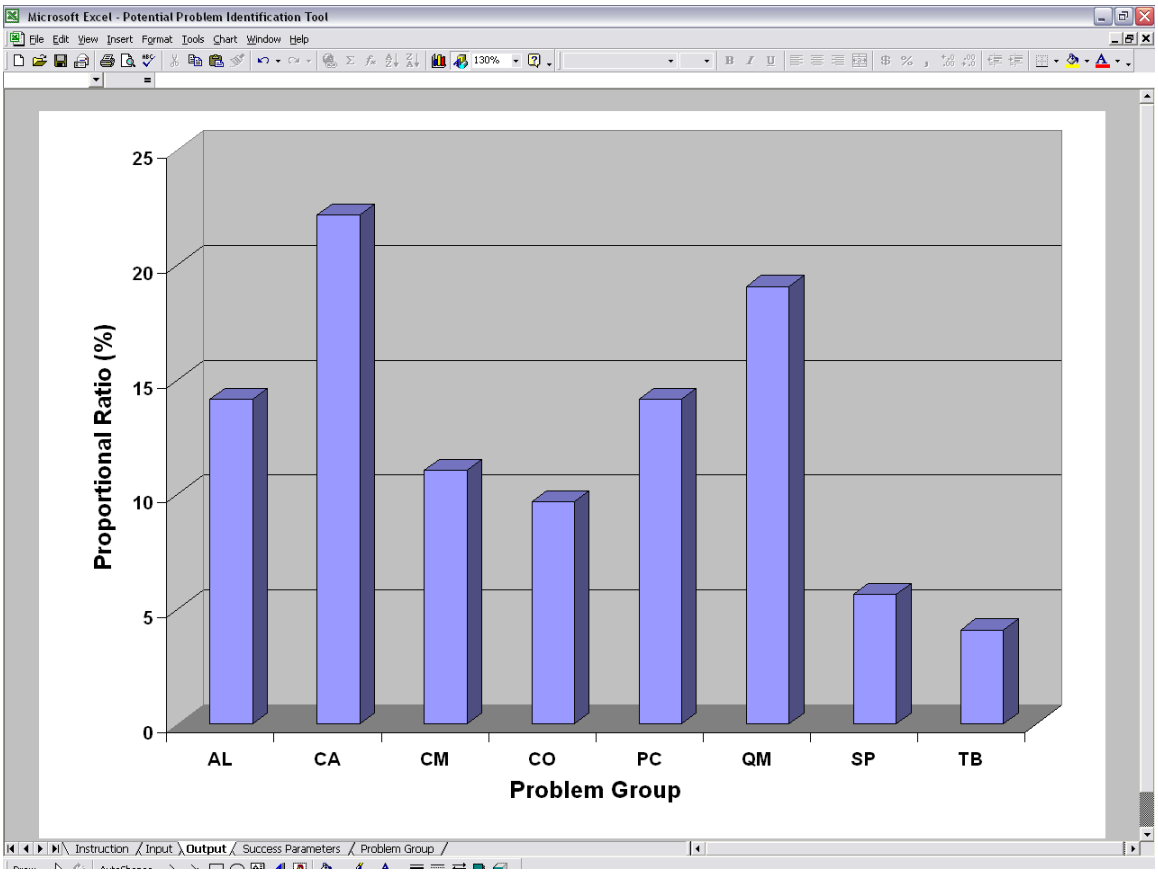


Figure 5-6. Screen capture of output worksheet of application

The histogram is drawn based on the proportional ratio of each problem group. During assessment of the project success parameter weights and problem groups, the aggregated scores will be computed as discussed in the section 5.3 using the proportional ratio of each success parameter weight. The aggregated scores indicate the degree of criticality of problem groups. But it is hard to tell how serious a problem group is and also there is a limitation in showing the

degrees of criticality. The proportional ratio of each problem group provides the big picture for all problem groups. Each ratio tells the proportion of itself with respect the total negative impact problem groups. The proportional ratio still provides the ranking with the degrees seriousness and criticality with respect to the total negative impact of problem groups. The interpretation of output format of the histogram is explained in the Instruction worksheet. Table 5-14 shows the computation of the proportional ratio of each problem group shown in Figure 5-6.

Table 5-14. Computation of proportional ratio of scores

Problem Group	Ranking	Aggregated Scores	Proportional Ratio			
AL	3	79	79/559	=	0.14	(14%)
CA	1	124	124/559	=	0.22	(22%)
CM	5	62	62/559	=	0.11	(11%)
CO	6	54	54/559	=	0.10	(10%)
PC	4	79	79/559	=	0.14	(14%)
QM	2	107	107/559	=	0.19	(19%)
SP	7	32	32/559	=	0.06	(6%)
TB	8	23	23/559	=	0.04	(4%)
Sum		559				

As shown in Table 5-14, the proportional ratio provides the proportion of each problem group into the total negative impact on the project and the ranking of each problem group. So the final user can tell the degrees of criticality of each problem group with respect to the overall project in qualitative as well as quantitative terms. According to Figure 5-6 and Table 5-14, CA and QM are the most critical problem groups and SP and TB are the least critical problem groups among eight problem groups.

In the Success Parameters and Problem Groups worksheet, the definitions of success parameters and problem groups are explained for those who are not familiar with their definitions.

Validation of Application

Overview

The potential problem identification tool is a decision-making aid, designed for use by project participants especially project managers and owners in the early phase of projects. Under given circumstances – priority weights of success parameters and expected problems severity, this tool will provide project participants with a deep insight of potential project problems. So it is necessary to validate this tool as a useful guideline for participants. The main output of this tool is to show the possible future problems based on the combination of priority weights of success parameters and problem severity. To validate this tool, the comparison of the output of tool of project problems and actual project problem cases is necessary. If the output of tool is close to the actual project case, then the tool will be validated. To do so, it is required to collect some information on projects such as priority weights of success parameters and severity of project problems, etc. It will be an intense process to validate the tool. There are numerous causes and reasons out there that affect the project performance. There is no perfect tool to forecast or predict every project problem, however, any tool that provides guidelines for solving project problems and improve performance at the early phase of projects should be welcome. In next section, the whole validation process is addressed, including the validation survey.

Validation survey

To compare the output of the tool and the actual project data, three criteria have to be included in the survey. They are 1) priority weights of project success; 2) degree of severity of project problems at the early phase of project or the time a participant joined the project; and 3) the actual critical problems at the end of project or at the project review phase. The first two criteria are necessary to calculate the values in the tool and the last criterion is needed to compare the output of tool. The first two criteria are based on the early stage of construction and

the last criterion is based on the end of project. In addition to this information, participants were asked to fill in their experience in the construction industry, their position, and the characteristics of projects they participate or participated in. The total duration for a project to be described in the survey is from the contract phase (0%) to the substantial completion (100%). Each participant is asked to fill in the time they joined the project and the time they leave the project using percentages in multiples of 10. If any participant joined the project at a stage earlier than the contract phase of project or at the contract phase, the value in the survey will be zero (0). If any participant left the project at the substantial completion or later than that time period, the value will be 100. It is very useful to see how long a participant works on a project to notice any changes in project problems during the whole project duration if any changes occur. One of the survey questions asked whether there were any changes in priority weight of project success parameters during the project period. Only one project has some changes in priority weights of its success parameters. So this information will be discarded in the validation process. A full set of survey questions is available in Appendix G.

The survey responses were analyzed using the previously described Microsoft Excel tool. Appendix G has the Instruction and Survey worksheet as shown in Figure G-1 through G-4.

Validation survey output

The total number of collected project data sets is six (6) for the tool validation process. One of them had some changes in the priority weights of the success parameters, but as stated earlier, these changes will not be used during the validation process. Each project is labeled as A, B, C, D, E, and F to protect the participants' identity. Table 5-15 shows the project characteristics and location, participants' number of years of experience, and duration of their participation on a project.

Table 5-15. General summary of participants and project characteristics

Project	Characteristics	Project Location	# of Years in Experience	Duration (%)		
				Joining (A)	Leaving (B)	Working (B-A)
A	Commercial & Government Facilities	Florida	10	0	100	100
B	Hospitalities & Residential	Florida	19	30	100	70
C	Government Facilities	Washington D.C.	7	0	100	100
D	Civil and Heavy	Korea, South	10	10	70	60
E	Civil and Heavy	Georgia	16	0	80	80
F	Commercial & Hospitalities	Florida	34	65	90	25

The characteristics of projects are various such as commercial, government facilities, hospitalities & residential, and heavy civil and highway. The six projects come from four different locations that are Florida, Washington D.C., Georgia, and South Korea. There are three (3) projects from Florida and one project is from each of the rest of the locations. The lowest number of years of experience is seven (7) and the highest number of years of experience is 34. Most participants join the project close to the contract time or earlier phase of construction and leave the project close to the substantial completion. The longest working duration is 100% from Project A and C and the shortest working duration is 25% from Project E.

To reassess the potential project problems using the tool, the priority weights of success parameters are necessary. Table 5-16 shows the priority weights of the six (6) projects.

Table 5-16. Priority weights of six projects

Project	Success Parameters				
	Cost	Schedule	Quality	Safety	Satisfaction
A	85	72	90	72	100
B	90	100	85	75	85
C	90	85	100	72	85
D	100	95	90	90	80
E	100	100	80	90	90
F	75	85	80	90	100

As shown in Table 5-16, each project has different priority weights for itself. Cost, schedule, satisfaction have two top priority over other success parameters. Quality has one top

priority over other parameters. Safety has no top priority over other parameters and most of them are marked as the lowest priority. Table 5-16 shows that each project has its own priorities for project success. It supports that there should be more research on the multi-project success parameters. Due to the variety of priority weights for success parameters and the number of success parameters involved for a project, the current norm for the project control concept may not be as accurate as it used to be. The current norm is as usual concerned about cost and schedule. But now there are more parameters other than just cost and schedule to be considered in classifying a project as successful in the construction industry.

The severity of the project problems of the six projects is shown in Table 5-17. The final critical ranking in the project review process or the time a participant leaves a project and the critical ranking computing from the application are shown in Table 5-17 as well. The highest severity is 100 for Project E and F. The problem groups are CO and PC for Project E and CA for Project F. The lowest severity is zero (0) for SP in Project A. The 'Review' column shows the critical ranking marked by the participant and the 'Tool' column is the computed critical ranking using the tool based on the survey input. The 'Difference' column shows the difference in ranking.

The easiest way to validate the tool is to compare the actual critical ranking assigned by a participant to the critical ranking resulting from the tool based upon the survey input. If the tool output is close to the actual output, then it will be a good validation of tool. If the output of tool were perfectly the same as the actual ranking, then the values in 'Difference' column of Table 5-17 will be zero (0). Even though the output from the tool is not exactly the same as the actual ranking, the output of the tool will be still validated if the values in the 'Difference' column in Table 5-17 are smaller. For example, a ranking from the tool is eighth and an actual ranking

Table 5-17. Comparison of actual project and tool output

Project	Problem		Critical Ranking		
	Group	Severity	Review (A)	Tool (B)	Difference (A-B)
A	AL	60	3	3	0
	CA	40	1	4	(3)
	CM	30	6	5	1
	CO	20	4	6	(2)
	PC	65	2	1	1
	QM	50	5	2	3
	SP	0	7	8	(1)
	TB	10	8	7	1
B	AL	90	1	1	0
	CA	20	4	5	(1)
	CM	20	5	6	(1)
	CO	10	6	8	(2)
	PC	60	3	3	0
	QM	40	7	4	3
	SP	20	8	7	1
	TB	70	2	2	0
C	AL	80	2	2	0
	CA	20	7	8	(1)
	CM	50	6	4	2
	CO	35	4	5	(1)
	PC	60	1	3	(2)
	QM	70	3	1	2
	SP	31	8	7	1
	TB	30	5	6	(1)
D	AL	30	6	6	0
	CA	40	4	4	0
	CM	50	3	3	0
	CO	35	5	5	0
	PC	80	1	2	(1)
	QM	70	2	1	1
	SP	20	7	7	0
	TB	5	8	8	0
E	AL	60	8	8	0
	CA	80	6	4	2
	CM	90	3	3	0
	CO	100	1	1	0
	PC	100	2	2	0
	QM	70	5	6	(1)
	SP	90	7	7	0
	TB	90	4	5	(1)
F	AL	50	4	7	(3)
	CA	100	1	1	0
	CM	60	7	5	2
	CO	30	6	8	(2)
	PC	40	8	6	2
	QM	80	3	2	1
	SP	90	2	3	(1)
	TB	70	5	4	1

is first for a problem group. The ranking difference will be seven. This is the maximum ranking difference between actual and tool output. In this case, the tool output may not be validated because the gap between actual and tool output is much different. But if the ranking difference between actual review and tool output is small enough such as one (1) or two (2), then the output of tool is still considered to being close enough to the actual ranking. The values in the 'Difference' column in Table 5-17 have the minimum of zero (0) and the maximum of three (3) in absolute value form. Only four problem groups have a three (3) difference out of 48 problem groups could be found and the rest of values in differences fall in the zero (0), one (1), or two (2) groups. The output of the tool predicts very close the actual ones.

In addition to the ranking difference between tool output and actual output for the validation of the tool, another way to validate the tool is to use a regression model. The evaluation of a regression model is to use the R^2 value (variability). The higher the R^2 value, the better the validation is for the model. A regression model for this case falls into the expectation or forecasting model. If all the values of actual critical ranking in Table 5-17 are on the y-axis and the values of tool critical rankings in Table 5-17 are on the x-axis, then a regression model with R^2 can be drawn as shown in Figure 5-7. The R^2 value of this regression model is 0.6747 (67.47%). It is not a high R^2 value but it is still serves validating the tool. The equation of this regression model is shown in Equation 5-1:

$$y = 0.8214x + 0.8036 \qquad \text{(Equation 5-1)}$$

where, y=actual critical ranking; x= tool critical ranking.

Even though there is a small difference in critical ranking as shown in Table 5-17, the R^2 value does not seem high. This is because the four (4) combination pairs of ranking have a difference of three (3), CA and QM in Project A, QM in Project B, and AL in Project F in Table 5-17.

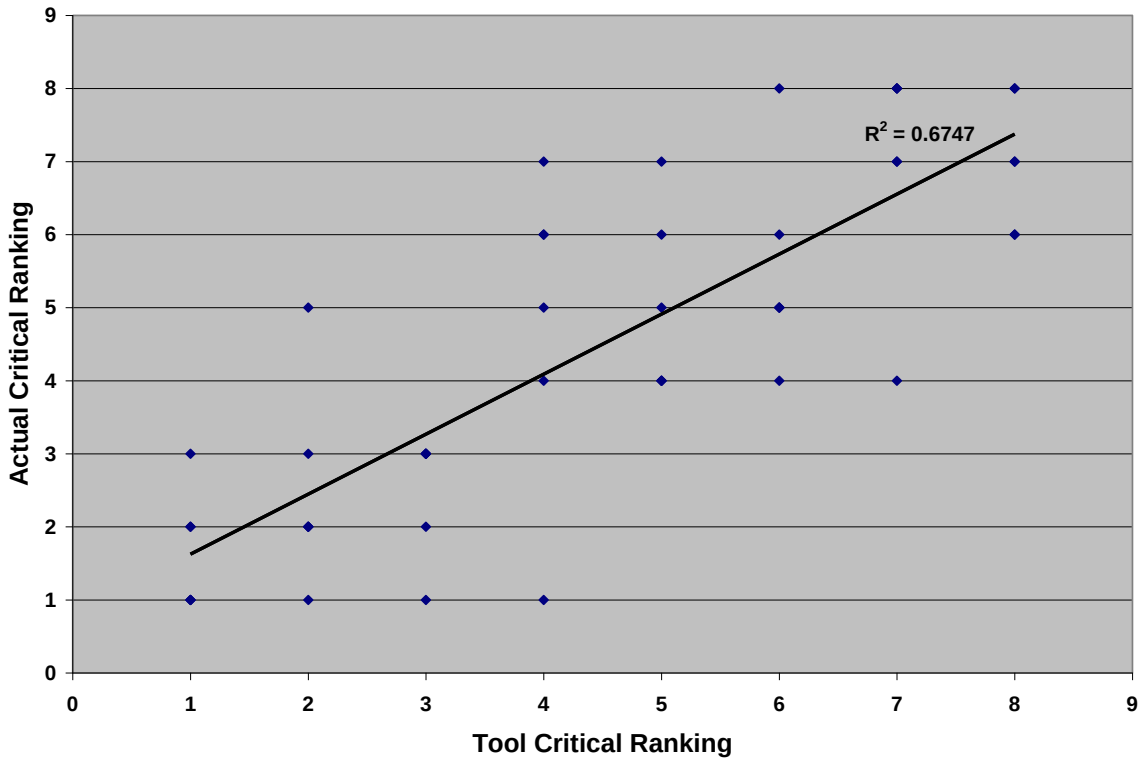


Figure 5-7. Regression model for validation of tool

These pairs are considered as outliers in the model that are far from the trend line in Figure 5-7. The further the distance from the trend line, the less the R^2 value is. If the regression model is redrawn without these four (4) pairs, the R^2 value of redrawn regression model will be increased to 0.7844 (78.44%) from 0.6747 (67.47%). This value is a lot higher than that of the original value. Therefore the original R^2 value is still a worthy validating tool. The redrawn regression model is shown in Appendix H.

As stated earlier in this section, there is no perfect reassessment tool. For example, a project manager considers some critical problems out of eight problem groups. But he/she does not consider all eight problem groups critical but he/she may consider the top three or four problem groups seriously. In this case, the critical ranking among the top three or four problem groups may not mean anything to him/her. In other words, three or four problem groups would be treated as one big critical group but not individual groups. Once he considers them all as

critical. From this perspective, the output of this tool is able to provide an overview of the critical problem groups based on the situations. Although, based on six case studies, this tool is not perfectly the same as the actual ranking, it still will be able to provide the potential assessment of project problems with a priority weight of success parameters.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Our society is getting more demanding in every aspect of our lives as technology has developed and our way of life has improved. It is hard for sellers or service providers to satisfy customers due to the high expectation from customers on the service. From this perspective, the construction industry has been changing rapidly as well. The customers (owners) have more demands on their service (construction) and the service providers (general contractors) try to keep the customers satisfied to have them come again for another service (repeat customers). The demands on service in construction come from two perspectives in terms of time. One is for the construction phase and something tangible and objective and the other is after the construction and something intangible and subjective. Within the five project success parameters, the first one is related to cost, schedule, and safety, while the second one is related to quality and satisfaction. Traditionally, cost and schedule are two favorite success parameters used for construction projects in order to classify them as a successful project. As discussed based on Table 5-16 most projects require more than cost and schedule to be successful with different priority weights. The priority weights depend heavily upon owners' requests and the characteristics of projects. It depicts a project manager's concern for all possible success parameters to meet the owner's demands and at the same time minimize the potential for current problems, in order to deliver a successful project. How well project problems are managed is the key to satisfying the customers. To do so, it is necessary to research the relationship between project success parameters and project problems and to integrate them as one project control and management perspective.

Many articles have been written about project management and controls and most of them are focused on cost and schedule as keys to success. These two parameters are clearly an objective measurement to judge the success of a project. This could be why many studies on cost and schedule have been conducted. On the other hand, there are not so many studies available on other parameters for project success. Besides cost and schedule, safety, quality, and satisfaction could be used, but they are subjective and they can be difficult to measure. Even though these parameters would be subjective and hard to measure, the request to satisfy these parameters in addition to cost and schedule are rising in the construction industry as shown in the data gathered in Table 5-16. In this study, the relationship between project success parameters and project problems are mainly discussed using various methods such as canonical correlations and factor analysis. During this process, project problems respond to each project success parameter differently. Their responses are not constant for the five project success parameters. Once the relationship between a project success parameter and project problems are defined using confirmatory factor analysis (CFA), this study performs the integration of five project success parameters as one project success parameter depending on their priority weights. To accomplish this, the SMART*S* (Edwards and Barron 1994) technique is applied. During this integration of the five project success parameters with their priority weights, all the relationships between a project success parameter and project problems are integrated as well. Based on the priority weights of the project success parameters, the potential critical problem groups can be identified. Lastly, the degree of problem severity is applied to the previous stage to reassess the critical project problem groups at the early phase of construction or earlier than that. Using this process, the project manager could identify the critical problem groups using the priority weights of the success parameters and the degree of problem severity the project faces.

The final output of this research is a simple measurement tool called Potential Problem Identification Tool. This tool is a decision-making aid for project managers at the early phase of a project. The tool gives you a degree of overview for being critical of project problems based on priority weights of success parameters and the degree of project problem severity. It will be helpful to projects managers in managing project problems when there are limited resources available to manage them. As mentioned in the validation process, this is a good guideline for a decision-making tool but not an absolute way for the selection of critical problem groups. Combining personal experience and this tool would result in the best selection of critical problems for a project.

Recommendations for Future Research

This research mainly concerns the relationships between project problems and project success parameters and its application. This study is not the first study of multi-project success parameters, but one of a few studies done so far. All the processes addressed in this study will be helpful for further studies on multi-project success parameters. There are five project success parameters discussed in this study and there could be more than five and possibly other kinds of parameters available.

Regarding project problem groups, this research focuses on the project problem group level but it may be necessary to study these relationships at the project problem level as well. Even though the project group level provides the overview of relationship between problem groups and success parameters, with respect to the applications of the results, there would be more potential ways at the project problem level, compared to the project group level. It will give more opportunities to study the relationship between project success parameters and problems in depth and provides more versatility in its application. If both project problem group level and project problem level are available, then the project problem group level would be

useful for the early phase of project to set up the overall direction of project. On the other hand, the project problem level would be useful for the project control during the whole period of project execution.

The main concept of the identification tool is to decide the weight of the priority of success parameters and to identify the degree of severity. Even though it is designed to assist a project manager in the decision-making process for the selection of critical problem groups under the given circumstances, the weights for success parameters and the degree of severity may not be the same among all project participants in the same project if all participants are asked to decide the weights of success parameters and the degree of severity because everybody has their own perspective of a project and interprets it in their ways. In this case, the output of a tool can be different for different participants. To minimize this discrepancy on perceptions for the usage of tool among project participants, even it is recommended that fuzzy weighting (Seo et al. 2004) investigated for ranking the priority of weights and the severity of problems. This could possibly result in less biased output to choose from for the project manager.

One of the objectives of this research is to define the relationship between project problems and project success parameters. Through this relationship, this research provides the guideline in identifying the potential project problems using the priorities of success weights and the degree of problem severities. The identification of potential problem groups for the project is a part of the project risk mitigation plans. The project risk is different for different project contracting strategies and project delivery methods. It means a problem does not have the same degree of negative impact for every contracting strategy and project delivery method all the time. A negative impact of a problem on a project in a lump sum contract may not be the same as the one in a cost plus contract. In addition to contracting strategy and project delivery, the project types

will be considered as well. A different type of project such as commercial, residential, industry, and heavy civil has its own characteristics to be concerned for a project success. If every type of project has a problem, then the negative impact of that problem cannot be the same to all different types of project because its impact on project could be different from the type of projects. The final output and application of the output for this research would be a boilerplate, but not a tailor-made for a specific type of contracting strategy, project delivery method, or project type. These issues should be explored in future studies, This research mainly focuses on the projects and practices in the United Sates. Every country has different culture and practices. It means that the output of current tool for a foreign country may not be as useful as here. With respect to the globalization, the research on overseas projects would provide deep insight into international project management.

APPENDIX A
43 POTENTIAL PROBLEMS

Table A-1. 43 Potential problems

No.	Group	Potential Problems
1	AL1	The project team is lacking in the necessary expertise, experience, breadth and depth to successfully execute the project.
2	TB1	The project team is experiencing a high turnover rate and instability in team membership.
3	CM1	The project teams response to Requests for Information, questions, and changing events that can significantly impact project results is slow, inadequate or very late.
4	PC1	The project team is losing confidence in the accuracy and validity of the schedule due to constantly changing activity durations and repeated slippages from one reporting period to the next.
5	PC2	Design milestones are not met and achieving future phases milestones are not confirmed in relation to the impact of factors beyond information provided in current progress and status reports.
6	CO1	Construction is bid or commences before completion of project design resulting in an incomplete scope definition at time of award.
7	AL2	Business goals, project objectives, and critical success factors are vague and/or inconsistent relative to project team and key stakeholder understanding.
8	CM2	Owner and/or contractor is requesting an excessive number of contract changes during project execution (detailed design, procurement, construction, and start up).
9	CO2	Project scope items are omitted from bid packages.
10	CO3	Some project participant companies are not financially stable.
11	QM1	The project is experiencing a high level of detailed engineering/design/specification errors and changes.
12	QM2	A project specific quality plan for construction is not completely developed that is consistent with the contract documents, including plans and specifications, and project participant roles and responsibilities.
13	QM3	The project fails to follow the quality plan for construction in relation to the roles and requirements of those who are responsible for that plan.
14	SP1	The project is experiencing a high level of safety incidents.
15	SP2	Design reviews fail to include qualified personnel that can analyze safety and loss prevention features of plans and specifications.
16	SP3	Project team personnel lack involvement in safety inspections, awareness of safety issues, and education in safety practices.
17	SP4	Potential safety related problems are not resolved in a timely manner.
18	SP5	Drastic actions (e.g., fines, dismissals, work stoppages) are often needed to address non-compliance in safety practices.
19	SP6	The project is not following the requirements of a project specific safety plan during construction.
20	TB2	Owner and contractor project personnel are not properly integrated into the project team.
21	CA1	The project lacks sufficient skilled craft and is experiencing high craft turnover due to competition from other projects, low wages, and shorter work schedules.

Table A-1. Continued

No.	Group	Potential Problems
22	CA2	The project lacks sufficient manpower, materials, small tools and construction equipment to adequately support planned activities.
23	AL3	The level of maintenance personnel involvement in detailed design is low and maintenance personnel are not aligned with other project team personnel with respect to maintenance issues for the facility.
24	CA3	The project is using new technology or construction practices that are unproven in commercial use.
25	CM3	The project team is failing to identify and/or address missing requirements during design reviews.
26	PC3	The level of detail and the scope covered in the budget estimate are not clear.
27	AL4	The project manager (or team leader) is lacking in the required level of experience and skills.
28	CM4	The project is not following an appropriate change management that includes defining cost and mark-up rates, evaluating schedule impact, and/or initiating dispute resolution procedures.
29	TB3	Key project stakeholder(s) is (are) exhibiting poor relationships and pursuing private agendas.
30	AL5	Commitments are increasingly not made with the intention of being met and are almost always not met.
31	PC4	The project is experiencing difficulties in integrating schedules between participants.
32	AL6	The project is asking vendors to perform functions outside their areas of expertise and experience.
33	SP7	Hazard and Operability (HAZOP) plan is late or is experiencing an excessive number of operational/support items that are not complete during the design phase.
34	TB4	The project team is not being encouraged to be realistic and truthful when project circumstances are unfavorable.
35	PC5	Actual installed bulk material quantities are greater than estimated or forecasted total bulk material quantities (e.g., steel, concrete, straight run pipe, electrical wire and cable)
36	PC6	Float for project activities is being used up at an increasingly high rate
37	PC7	Actual schedule activities are lagging behind planned schedule activities over several reporting periods
38	PC8	Forecasts-to-complete based on actual project experience, actual commitments, and actual expenditures are projecting overruns.
39	QM4	The project is experiencing an above normal level of construction rework hours and costs when compared to target levels of rework included in the total budget or schedule.
40	QM5	Project quality control results are reflecting high rejection rates for equipment and materials under fabrication in the factory and/or materials in place through testing in the field.
41	AL7	The project is experiencing difficulties due to the lack of understanding cultural differences.
42	CA4	Material and/or equipment prices are increasing rapidly for certain types of materials/equipment that represent a high percent of the project cost.
43	AL8	The client and/or upper management is frequently making unreasonable requests (includes setting unrealistic goals).

APPENDIX B
DEFINITION OF EACH PROBLEM GROUP

- Alignment (AL): These are practices associated with the overall alignment of the project team with respect to project goals and objectives. The make-up of project teams can change considerably from the Pre-Project Planning Phase to the Execution Phase. The owner project team generally changes from business planning personnel to those responsible for implementation. New contractors and suppliers are also usually added at this time. Both owner and contractor teams are generally expanded to address the increasing volume of work. How these new team members and contractors understand and are aligned to common goals plays key role to project success.

- Constructability (CA): Constructability generally involves construction related methodology and planning. The ability to efficiently plan and execute the construction of a facility is a major driver behind project success.

- Change Management (CM): CII and others have accumulated large amounts of research regarding the effects of late project scope changes and high volumes of rework to poor project outcomes. How the project team makes decisions on, controls, tracks, and implements change on a project can have a significant effect on project outcomes.

- Contracting (CO): Contracting in terms of a practice is based on the matching of contract types to project risks. It is not an endorsement of any one particular contract type. There is no weighting of the tool that values Turnkey versus Lump Sum versus Design-Build versus Cost Reimbursable. It is purely a measure of whether the project team is seeing potential issues between the contracts in place and the scope that needs to be executed.

- Project Control (PC): Project control involves the tools and techniques used to track, evaluate and improve schedule and cost performance. In terms of this tool, it is not simply the use of a project schedule and cost reporting. It is a measure of how accurate the schedule is; how effective the schedule is in tracking work and identifying gaps; whether the cost reporting is utilized in future decision making; and whether or not the team is effectively using the information as a planning tool. Too often, schedule and cost reports become deliverables themselves instead of tools to be used in planning the work.

- Quality Management (QM): Quality Management includes items such as quality of engineering, construction quality and rework, equipment inspections and testing and facility start-up.

- Safety Practices (SP): This is a measure of whether or not the project team is fully engaged in the practices that drive project safety (see CII Target Zero practices).

- Team Building (TB): People implement projects. The core competencies of the people that constitute the project team and how the people that make-up the project team play a very key role in the success of any project. Good project teams overcome gaps in scope, risk events, design issues, project changes etc., in a proactive way to minimize the negative effects on project outcomes. Poor teams do not.

APPENDIX C
DESCRIPTIVE STATISTICS OF 43 PROBLEMS

Table C-1. Descriptive statistics of 43 problems

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
	Cost	542	5.42	0.619	11.43
	Schedule	540	5.40	0.600	11.11
AL1	Quality	507	5.07	0.803	15.84
	Safety	471	4.71	1.211	25.71
	Satisfaction	522	5.22	0.844	16.16
	Cost	481	4.81	0.880	18.29
	Schedule	475	4.75	0.187	18.68
AL2	Quality	451	4.51	1.063	23.57
	Safety	353	3.53	0.421	42.10
	Satisfaction	491	4.91	1.150	23.42
	Cost	404	4.04	1.019	25.22
	Schedule	403	4.03	1.053	26.13
AL3	Quality	496	4.96	0.999	20.15
	Safety	335	3.35	1.284	38.31
	Satisfaction	466	4.66	0.839	18.01
	Cost	491	4.91	0.801	16.32
	Schedule	504	5.04	0.871	17.28
AL4	Quality	433	4.33	1.158	26.75
	Safety	406	4.06	1.256	30.92
	Satisfaction	484	4.84	0.967	19.97
	Cost	472	4.72	1.001	21.20
	Schedule	528	5.28	0.991	18.76
AL5	Quality	403	4.03	1.300	32.25
	Safety	353	3.53	1.374	38.94
	Satisfaction	499	4.99	1.109	22.22
	Cost	457	4.57	1.003	21.94
	Schedule	456	4.56	0.840	18.43
AL6	Quality	507	5.07	0.886	17.48
	Safety	414	4.14	1.289	31.12
	Satisfaction	434	4.34	1.124	25.91
	Cost	400	4.00	1.208	30.21
	Schedule	422	4.22	1.180	27.95
AL7	Quality	395	3.95	1.299	32.89
	Safety	416	4.16	1.239	29.78
	Satisfaction	419	4.19	1.391	33.19
	Cost	471	4.71	1.143	24.26
AL8	Schedule	487	4.87	1.074	22.05
	Quality	401	4.01	1.269	31.64

Table C-1. Continued

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
AL8	Safety	381	3.81	1.339	35.15
	Satisfaction	484	4.84	1.155	23.87
	Cost	497	4.97	0.877	17.65
	Schedule	528	5.28	0.884	16.74
CA1	Quality	491	4.91	1.059	21.57
	Safety	455	4.55	1.071	23.54
	Satisfaction	474	4.74	1.036	21.85
	Cost	471	4.71	1.032	21.92
	Schedule	548	5.48	0.842	15.37
CA2	Quality	428	4.28	1.273	29.75
	Safety	424	4.24	1.258	29.67
	Satisfaction	464	4.64	1.063	22.91
	Cost	469	4.69	1.055	22.50
	Schedule	457	4.57	1.160	25.38
CA3	Quality	446	4.46	1.220	27.35
	Safety	416	4.16	1.181	28.39
	Satisfaction	427	4.27	1.173	27.48
	Cost	562	5.62	0.596	10.61
	Schedule	403	4.03	1.100	27.29
CA4	Quality	340	3.40	1.175	34.55
	Safety	256	2.56	1.098	42.90
	Satisfaction	455	4.55	1.135	24.94
	Cost	507	5.07	0.840	16.56
	Schedule	532	5.32	0.786	14.77
CM1	Quality	431	4.31	0.945	21.94
	Safety	326	3.26	1.213	37.22
	Satisfaction	466	4.66	1.142	24.51
	Cost	548	5.48	0.818	14.93
	Schedule	522	5.22	1.016	19.46
CM2	Quality	403	4.03	1.144	28.39
	Safety	321	3.21	1.314	40.93
	Satisfaction	486	4.86	1.158	23.82
	Cost	510	5.10	0.671	13.15
	Schedule	488	4.88	0.778	15.95
CM3	Quality	473	4.73	1.066	22.54
	Safety	332	3.32	1.232	37.11
	Satisfaction	469	4.69	1.055	22.50
	Cost	539	5.39	0.720	13.35
CM4	Schedule	527	5.27	0.786	14.91
	Quality	389	3.89	1.256	32.29

Table C-1. Continued

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
CM4	Safety	287	2.87	1.238	43.14
	Satisfaction	492	4.92	1.007	20.46
	Cost	537	5.37	0.730	13.60
	Schedule	497	4.97	0.877	17.65
CO1	Quality	385	3.85	1.099	28.54
	Safety	306	3.06	1.094	35.75
	Satisfaction	435	4.35	1.043	23.97
	Cost	554	5.54	0.590	10.65
	Schedule	527	5.27	0.847	16.07
CO2	Quality	424	4.24	1.258	29.67
	Safety	312	3.12	1.329	42.59
	Satisfaction	490	4.90	1.127	23.00
	Cost	472	4.72	1.068	22.64
	Schedule	496	4.96	0.937	18.90
CO3	Quality	417	4.17	1.241	29.77
	Safety	362	3.62	1.362	37.63
	Satisfaction	454	4.54	1.117	24.61
	Cost	468	4.68	0.915	19.56
	Schedule	559	5.59	0.722	12.92
PC1	Quality	350	3.50	1.261	36.03
	Safety	318	3.18	1.244	39.12
	Satisfaction	479	4.79	0.941	19.65
	Cost	496	4.96	0.836	16.85
	Schedule	563	5.63	0.560	9.94
PC2	Quality	360	3.60	1.039	28.87
	Safety	298	2.98	1.095	36.75
	Satisfaction	488	4.88	0.941	19.28
	Cost	537	5.37	0.770	14.34
	Schedule	471	4.71	0.941	19.98
PC3	Quality	400	4.00	1.068	26.69
	Safety	287	2.87	1.222	42.58
	Satisfaction	487	4.87	1.036	21.27
	Cost	443	4.43	0.863	19.49
	Schedule	538	5.38	0.732	13.60
PC4	Quality	354	3.54	1.268	35.83
	Safety	325	3.25	1.169	35.98
	Satisfaction	449	4.49	1.153	25.68
	Cost	539	5.39	0.733	13.61
PC5	Schedule	453	4.53	1.135	25.06
	Quality	318	3.18	1.220	38.35

Table C-1. Continued

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
PC5	Safety	261	2.61	1.057	40.51
	Satisfaction	417	4.17	1.327	31.82
	Cost	441	4.41	1.114	25.27
	Schedule	537	5.37	1.016	18.93
PC6	Quality	325	3.25	1.268	39.01
	Safety	293	2.93	1.151	39.29
	Satisfaction	427	4.27	1.103	25.84
	Cost	450	4.50	0.943	20.96
	Schedule	560	5.60	0.632	11.29
PC7	Quality	327	3.27	1.057	32.32
	Safety	297	2.97	1.053	35.46
	Satisfaction	463	4.63	0.891	19.23
	Cost	556	5.56	0.739	13.29
	Schedule	492	4.92	1.046	21.26
PC8	Quality	357	3.57	1.160	32.49
	Safety	297	2.97	1.118	37.63
	Satisfaction	500	5.00	1.058	21.17
	Cost	539	5.39	0.646	11.99
	Schedule	519	5.19	0.771	14.85
QM1	Quality	471	4.71	1.032	21.92
	Safety	311	3.11	1.224	39.35
	Satisfaction	489	4.89	1.122	22.94
	Cost	442	4.42	0.862	19.51
	Schedule	412	4.12	1.003	24.34
QM2	Quality	507	5.07	0.919	18.13
	Safety	275	2.75	1.143	41.58
	Satisfaction	452	4.52	0.995	22.01
	Cost	418	4.18	0.963	23.04
	Schedule	405	4.05	0.994	24.54
QM3	Quality	512	5.12	0.909	17.75
	Safety	301	3.01	1.253	41.63
	Satisfaction	447	4.47	1.044	23.35
	Cost	536	5.36	0.714	13.33
	Schedule	511	5.11	0.823	16.11
QM4	Quality	427	4.27	1.173	27.48
	Safety	313	3.13	1.074	34.31
	Satisfaction	459	4.59	1.030	22.45
	Cost	478	4.78	0.934	19.53
QM5	Schedule	532	5.32	0.676	12.72
	Quality	504	5.04	1.104	21.90

Table C-1. Continued

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
QM5	Safety	303	3.03	1.253	41.34
	Satisfaction	476	4.76	1.097	23.04
	Cost	449	4.49	1.082	24.09
	Schedule	440	4.40	1.140	25.91
SP1	Quality	351	3.51	1.367	38.96
	Safety	585	5.85	0.572	9.78
	Satisfaction	496	4.96	1.104	22.25
	Cost	424	4.24	0.971	22.90
	Schedule	401	4.01	1.100	27.43
SP2	Quality	416	4.16	1.317	31.66
	Safety	520	5.20	0.970	18.64
	Satisfaction	449	4.49	1.063	23.67
	Cost	383	3.83	1.068	27.89
	Schedule	367	3.67	1.049	28.59
SP3	Quality	356	3.56	1.267	35.60
	Safety	556	5.56	0.637	11.47
	Satisfaction	437	4.37	1.163	26.62
	Cost	398	3.98	1.058	26.59
	Schedule	401	4.01	1.145	28.54
SP4	Quality	344	3.44	1.219	35.44
	Safety	562	5.62	0.579	10.31
	Satisfaction	465	4.65	1.143	24.59
	Cost	441	4.41	1.226	27.79
	Schedule	464	4.64	1.204	25.96
SP5	Quality	393	3.93	1.336	34.00
	Safety	554	5.54	0.842	15.19
	Satisfaction	466	4.66	1.227	26.32
	Cost	390	3.90	1.196	30.66
	Schedule	398	3.98	1.183	29.72
SP6	Quality	344	3.44	1.177	34.23
	Safety	562	5.62	0.596	10.61
	Satisfaction	453	4.53	1.162	25.64
	Cost	437	4.37	1.064	24.36
	Schedule	452	4.52	1.034	22.88
SP7	Quality	438	4.38	1.215	27.73
	Safety	438	4.38	1.377	31.43
	Satisfaction	444	4.44	1.244	28.01
	Cost	468	4.68	0.937	20.02
TB1	Schedule	488	4.88	0.920	18.84
	Quality	457	4.57	1.022	22.37

Table C-1. Continued

No.	Outcome	Total Sum	Mean	S.D[1]	C.V[2]
TB1	Safety	397	3.97	1.220	30.74
	Satisfaction	477	4.77	1.018	21.35
	Cost	423	4.23	0.926	21.89
	Schedule	443	4.43	0.993	22.40
TB2	Quality	412	4.12	1.211	29.38
	Safety	354	3.54	1.292	36.49
	Satisfaction	473	4.73	1.076	22.74
	Cost	459	4.59	1.059	23.08
	Schedule	453	4.53	1.063	23.46
TB3	Quality	402	4.02	1.334	33.18
	Safety	345	3.45	1.459	42.28
	Satisfaction	510	5.10	1.063	20.84
	Cost	481	4.81	1.036	21.54
	Schedule	504	5.04	0.958	19.01
TB4	Quality	415	4.15	1.236	29.78
	Safety	387	3.87	1.309	33.82
	Satisfaction	507	5.07	0.951	18.76

Notes: 1. Standard Deviation. 2: Coefficient of Variation

APPENDIX D
SUMMARY OF CRITICAL RATIO (CR) METHOD PROCEDURE

Table D-1. Cost

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
AL	0.007	CO	0.003	CM	0.233				
CA	0.007	CO	0.003	CM	0.233				
CM	0.007	CO	0.003	CA	0.001				
CO	0.007	TB	0.065						
PC	0.007	CO	0.003	CM	0.233				
QM	0.007	TB	0.065						
SP	0.007	CO	0.003	CM	0.233				
TB	0.007	CO	0.003	QM	0.016				

Table D-2. Quality

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
AL	***	QM	***	CA	***	CO	***	PC	0.069
CA	***	QM	***	CO	***	CM	***	SP	0.001
CM	***	QM	***	CA	***	CO	***	PC	0.069
CO	***	QM	***	CA	***	SP	0.061		
PC	***	QM	***	CA	***	CO	***	CM	0.002
QM	***	CA	0.001	CO	0.004	CM	0.014	PC	0.259
SP	***	QM	***	CA	***	CO	***	PC	0.069
TB	***	QM	***	CA	***	CO	***	PC	0.069

Table D-3. Safety

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
AL	***	SP	***	CO	***	TB	0.010	CA	0.568
CA	***	SP	***	CO	***	CM	***	TB	0.003
CM	***	SP	***	CO	***	AL	***	TB	0.513
CO	***	SP	***	TB	0.067				
PC	***	SP	***	TB	0.067				
QM	***	SP	***	TB					
SP	***	CO	***	TB	***	AL	0.108		
TB	***	SP	***	CO	***	AL	***	CA	0.081

Table D-4. Satisfaction

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
AL	0.002	CO	***	SP	0.001	TB	0.024	QM	0.361
CA	0.002	QM	0.001	CO	***	TB	0.012	CM	0.545

Table D-4. Continued

Base	First		Second		Third		Fourth		Fifth
	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value	Del. Var	P Value
CM	0.002	QM	0.001	TB	0.029	SP	0.251		
CO	0.002	SP	0.004	TB	0.044	CA	0.180		
PC	0.002	CO	***	QM	***	TB	0.012	SP	0.361
QM	0.002	TB	0.040	SP	0.044	CM	0.071		
SP	0.002	QM	0.001	TB	0.029	CM	0.085		
TB	0.002	QM	0.001	SP	0.025	CO	0.005	CM	0.007

APPENDIX E
SUMMARY OF RAW ESTIMATE AND ITS UNIQUE VARIANCES

Table E-1. Cost

AL Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.058	0.188	5.626	***
SP	←	Cost	1.283	0.135	9.508	***
QM	←	Cost	0.969	0.089	10.870	***
PC	←	Cost	0.990	0.095	10.476	***
CO	←	Cost	0.671	0.113	5.961	***
CA	←	Cost	0.889	0.125	7.083	***
AL	←	Cost	1.000			

CA Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.190	0.215	5.526	***
SP	←	Cost	1.443	0.161	8.941	***
QM	←	Cost	1.090	0.163	6.667	***
PC	←	Cost	1.114	0.111	10.029	***
CO	←	Cost	0.755	0.164	4.613	***
CA	←	Cost	1.000			
AL	←	Cost	1.125	0.159	7.083	***

CO Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.576	0.408	3.864	***
SP	←	Cost	1.911	0.368	5.192	***
QM	←	Cost	1.443	0.233	6.192	***
PC	←	Cost	1.475	0.270	5.460	***
CO	←	Cost	1.000			
CA	←	Cost	1.324	0.287	4.613	***
AL	←	Cost	1.490	0.250	5.961	***

PC Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.068	0.169	6.304	***
SP	←	Cost	1.295	0.108	12.040	***
QM	←	Cost	0.978	0.117	8.336	***
PC	←	Cost	1.000			
CO	←	Cost	0.678	0.124	5.460	***
CA	←	Cost	0.897	0.089	10.029	***

Table E-1. Continued

PC Base Continued

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
AL	←	Cost	1.010	0.096	10.476	***

QM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.092	0.251	4.344	***
SP	←	Cost	1.324	0.170	7.807	***
QM	←	Cost	1.000			
PC	←	Cost	1.023	0.123	8.336	***
CO	←	Cost	0.693	0.112	6.192	***
CA	←	Cost	0.918	0.138	6.667	***
AL	←	Cost	1.032	0.095	10.870	***

SP Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	0.825	0.120	6.890	***
SP	←	Cost	1.000			
QM	←	Cost	0.755	0.097	7.806	***
PC	←	Cost	0.772	0.064	12.040	***
CO	←	Cost	0.523	0.101	5.192	***
CA	←	Cost	0.693	0.077	8.941	***
AL	←	Cost	0.779	0.082	9.508	***

TB Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Cost	1.000			
SP	←	Cost	1.212	0.176	6.890	***
QM	←	Cost	0.915	0.211	4.344	***
PC	←	Cost	0.936	0.148	6.304	***
CO	←	Cost	0.634	0.164	3.864	***
CA	←	Cost	0.840	0.152	5.526	***
AL	←	Cost	0.945	0.168	5.626	***

Unique Variance

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	(er08)	0.153	0.030	5.110	***
SP	(er07)	0.198	0.026	7.576	***
QM	(er06)	0.083	0.016	5.121	***
PC	(er05)	0.078	0.011	7.104	***
CO	(er04)	0.204	0.029	7.129	***

Table E-1. Continued

Unique Variance Continued

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
CA	(er02)	0.096	0.017	5.728	***
AL	(er01)	0.074	0.011	6.788	***

Table E-2. Schedule

AL Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.080	0.070	15.492	***
QM	←	Schedule	1.057	0.082	12.812	***
PC	←	Schedule	0.775	0.075	10.281	***
CO	←	Schedule	0.963	0.118	8.169	***
CM	←	Schedule	0.906	0.080	11.390	***
CA	←	Schedule	0.594	0.185	3.204	0.001
AL	←	Schedule	1.000			

CA Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.820	0.571	3.187	
QM	←	Schedule	1.780	0.590	3.015	***
PC	←	Schedule	1.306	0.440	2.966	***
CO	←	Schedule	1.622	0.584	2.777	***
CM	←	Schedule	1.527	0.422	3.614	***
CA	←	Schedule	1.000			***
AL	←	Schedule	1.685	0.526	3.205	***

CM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.192	0.119	10.052	***
QM	←	Schedule	1.166	0.119	9.794	***
PC	←	Schedule	0.856	0.110	7.809	***
CO	←	Schedule	1.063	0.148	7.201	***
CM	←	Schedule	1.000			
CA	←	Schedule	0.655	0.181	3.614	***
AL	←	Schedule	1.103	0.097	11.390	***

CO Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.122	0.142	7.911	***

Table E-2. Continued

CO Base Continued

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
QM	←	Schedule	1.097	0.115	9.561	***
PC	←	Schedule	0.805	0.111	7.229	***
CO	←	Schedule	1.000			
CM	←	Schedule	0.941	0.131	7.201	***
CA	←	Schedule	0.616	0.222	2.777	0.005
AL	←	Schedule	1.038	0.127	8.169	***

PC Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.393	0.136	10.284	***
QM	←	Schedule	1.363	0.142	9.630	***
PC	←	Schedule	1.000			
CO	←	Schedule	1.242	0.172	7.229	***
CM	←	Schedule	1.169	0.150	7.809	***
CA	←	Schedule	0.766	0.258	2.966	0.003
AL	←	Schedule	1.290	0.125	10.281	***

QM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.022	0.097	10.495	***
QM	←	Schedule	1.000			
PC	←	Schedule	0.734	0.076	9.630	***
CO	←	Schedule	0.911	0.095	9.561	***
CM	←	Schedule	0.858	0.088	9.794	***
CA	←	Schedule	0.562	0.186	3.015	0.003
AL	←	Schedule	0.946	0.074	12.812	***

TB Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Schedule	1.000			
QM	←	Schedule	0.978	0.093	10.495	***
PC	←	Schedule	0.718	0.070	10.284	***
CO	←	Schedule	0.891	0.113	7.911	***
CM	←	Schedule	0.839	0.083	10.052	***
CA	←	Schedule	0.549	0.172	3.187	0.001
AL	←	Schedule	0.926	0.060	15.492	***

Table E-2. Continued

Unique Variance

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	(er08)	0.108	0.022	4.953	***
QM	(er06)	0.103	0.019	5.362	***
PC	(er05)	0.112	0.020	5.654	***
CO	(er04)	0.194	0.029	6.780	***
CM	(er03)	0.099	0.025	3.962	***
CA	(er02)	0.250	0.062	4.045	***
AL	(er01)	0.079	0.012	6.598	***

Table E-3. Quality

AL Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.267	0.093	13.578	***
SP	←	Quality	1.138	0.107	10.646	***
QM	←	Quality	0.634	0.091	7.008	***
CO	←	Quality	0.961	0.112	8.609	***
CM	←	Quality	1.021	0.088	11.587	***
CA	←	Quality	0.967	0.122	7.928	***
AL	←	Quality	1.000			

CA Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.311	0.166	7.893	***
SP	←	Quality	1.178	0.164	7.163	***
QM	←	Quality	0.656	0.116	5.677	***
CO	←	Quality	0.994	0.154	6.433	***
CM	←	Quality	1.056	0.142	7.432	***
CA	←	Quality	1.000			
AL	←	Quality	1.035	0.131	7.928	***

CM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.242	0.108	11.481	***
SP	←	Quality	1.116	0.117	9.529	***
QM	←	Quality	0.622	0.093	6.658	***
CO	←	Quality	0.941	0.118	7.984	***
CM	←	Quality	1.000			
CA	←	Quality	0.947	0.127	7.432	***
AL	←	Quality	0.980	0.085	11.587	***

Table E-3. Continued

CO Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.319	0.154	8.565	***
SP	←	Quality	1.185	0.155	7.654	***
QM	←	Quality	0.660	0.112	5.912	***
CO	←	Quality	1.000			
CM	←	Quality	1.062	0.133	7.984	***
CA	←	Quality	1.006	0.156	6.433	***
AL	←	Quality	1.041	0.121	8.609	***

QM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.997	0.286	6.984	***
SP	←	Quality	1.795	0.278	6.463	***
QM	←	Quality	1.000			
CO	←	Quality	1.514	0.256	5.912	***
CM	←	Quality	1.609	0.242	6.658	***
CA	←	Quality	1.524	0.268	5.677	***
AL	←	Quality	1.576	0.225	7.008	***

SP Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.113	0.105	10.563	***
SP	←	Quality	1.000			
QM	←	Quality	0.557	0.086	6.463	***
CO	←	Quality	0.844	0.110	7.654	***
CM	←	Quality	0.896	0.094	9.529	***
CA	←	Quality	0.849	0.119	7.163	***
AL	←	Quality	0.878	0.083	10.646	***

TB Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Quality	1.000			
SP	←	Quality	0.898	0.085	10.563	***
QM	←	Quality	0.501	0.072	6.984	***
CO	←	Quality	0.758	0.089	8.565	***
CM	←	Quality	0.805	0.070	11.481	***
CA	←	Quality	0.763	0.097	7.893	***
AL	←	Quality	0.789	0.058	13.578	***

Table E-3. Continued

Unique Variance

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	(er08)	0.159	0.032	5.011	***
SP	(er07)	0.303	0.049	6.194	***
QM	(er06)	0.273	0.040	6.749	***
CO	(er04)	0.382	0.058	6.565	***
CM	(er03)	0.188	0.032	5.938	***
CA	(er02)	0.474	0.071	6.652	***
AL	(er01)	0.093	0.019	4.890	***

Table E-4. Safety

CA Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	0.304	0.057	5.334	***
QM	←	Safety	1.259	0.099	12.707	***
PC	←	Safety	1.127	0.084	13.479	***
CO	←	Safety	1.161	0.112	10.351	***
CM	←	Safety	1.219	0.105	11.632	***
CA	←	Safety	1.000			

CM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	0.250	0.046	5.410	***
QM	←	Safety	1.033	0.075	13.844	***
PC	←	Safety	0.925	0.062	14.854	***
CO	←	Safety	0.952	0.087	10.939	***
CM	←	Safety	1.000			
CA	←	Safety	0.820	0.071	11.632	***

CO Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	0.262	0.050	5.262	***
QM	←	Safety	1.085	0.092	11.819	***
PC	←	Safety	0.971	0.078	12.434	***
CO	←	Safety	1.000			
CM	←	Safety	1.050	0.096	10.939	***
CA	←	Safety	0.862	0.083	10.351	***

Table E-4. Continued

PC Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	.270	0.049	5.566	***
QM	←	Safety	1.117	0.065	17.271	***
PC	←	Safety	1.000			
CO	←	Safety	1.030	0.083	12.434	***
CM	←	Safety	1.081	0.073	14.854	***
CA	←	Safety	0.887	0.066	13.479	***

QM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	0.242	0.044	5.507	***
QM	←	Safety	1.000			
PC	←	Safety	0.896	0.052	17.271	***
CO	←	Safety	0.922	0.078	11.819	***
CM	←	Safety	0.968	0.070	13.844	***
CA	←	Safety	0.794	0.063	12.707	***

SP Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	←	Safety	1.000			
QM	←	Safety	4.134	0.751	5.507	***
PC	←	Safety	3.702	0.665	5.566	***
CO	←	Safety	3.811	0.724	5.262	***
CM	←	Safety	4.003	0.740	5.410	***
CA	←	Safety	3.284	0.616	5.334	***

Unique Variance

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
SP	(er07)	0.145	0.021	6.929	***
QM	(er06)	0.155	0.030	5.220	***
PC	(er05)	0.077	0.019	4.157	***
CO	(er04)	0.348	0.055	6.376	***
CM	(er03)	0.237	0.040	5.951	***
CA	(er02)	0.209	0.034	6.217	***

Table E-5. Satisfaction

CA Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.763	0.076	10.046	***
SP	←	Satisfaction	0.986	0.062	16.026	***
QM	←	Satisfaction	0.778	0.066	11.801	***
PC	←	Satisfaction	0.963	0.050	19.259	***
CO	←	Satisfaction	0.844	0.064	13.107	***
CM	←	Satisfaction	1.013	0.057	17.706	***
CA	←	Satisfaction	1.000			

CM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.753	0.075	9.985	***
SP	←	Satisfaction	0.973	0.065	14.906	***
QM	←	Satisfaction	0.768	0.063	12.175	***
PC	←	Satisfaction	0.951	0.048	20.022	***
CO	←	Satisfaction	0.834	0.058	14.398	***
CM	←	Satisfaction	1.000			
CA	←	Satisfaction	0.988	0.056	17.707	***

CO Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.903	0.097	9.336	***
SP	←	Satisfaction	1.167	0.088	13.219	***
QM	←	Satisfaction	0.921	0.065	14.221	***
PC	←	Satisfaction	1.141	0.076	14.929	***
CO	←	Satisfaction	1.000			
CM	←	Satisfaction	1.199	0.083	14.398	***
CA	←	Satisfaction	1.184	0.090	13.107	***

PC Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.792	0.072	10.965	***
SP	←	Satisfaction	1.023	0.065	15.697	***
QM	←	Satisfaction	0.808	0.055	14.605	***
PC	←	Satisfaction	1.000			
CO	←	Satisfaction	0.877	0.059	14.929	***
CM	←	Satisfaction	1.051	0.053	20.022	***
CA	←	Satisfaction	1.038	0.054	19.259	***

Table E-5. Continued

QM Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.980	0.109	9.017	***
SP	←	Satisfaction	1.267	0.110	11.518	***
QM	←	Satisfaction	1.000			
PC	←	Satisfaction	1.238	0.085	14.605	***
CO	←	Satisfaction	1.085	0.076	14.221	***
CM	←	Satisfaction	1.301	0.107	12.172	***
CA	←	Satisfaction	1.285	0.109	11.801	***

SP Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	0.774	0.090	8.566	***
SP	←	Satisfaction	1.000			
QM	←	Satisfaction	0.789	0.069	11.518	***
PC	←	Satisfaction	0.977	0.062	15.697	***
CO	←	Satisfaction	0.857	0.065	13.219	***
CM	←	Satisfaction	1.027	0.069	14.906	***
CA	←	Satisfaction	1.014	0.063	16.026	***

TB Base

Problem Groups			Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	←	Satisfaction	1.000			
SP	←	Satisfaction	1.292	0.151	8.566	***
QM	←	Satisfaction	1.020	0.113	9.016	***
PC	←	Satisfaction	1.263	0.115	10.965	***
CO	←	Satisfaction	1.107	0.119	9.336	***
CM	←	Satisfaction	1.327	0.133	9.985	***
CA	←	Satisfaction	1.311	0.130	10.046	***

Unique Variance

Problem Groups		Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P Value
TB	(er08)	0.240	0.034	7.047	***
SP	(er07)	0.205	0.035	5.870	***
QM	(er06)	0.133	0.022	5.959	***
PC	(er05)	0.078	0.016	4.771	***
CO	(er04)	0.143	0.026	5.433	***
CM	(er03)	0.099	0.031	3.181	0.001
CA	(er02)	0.086	0.035	2.431	0.015

APPENDIX F
PLOTS OF TEN PAIRS OF PROJECT SUCCESS PARAMETERS

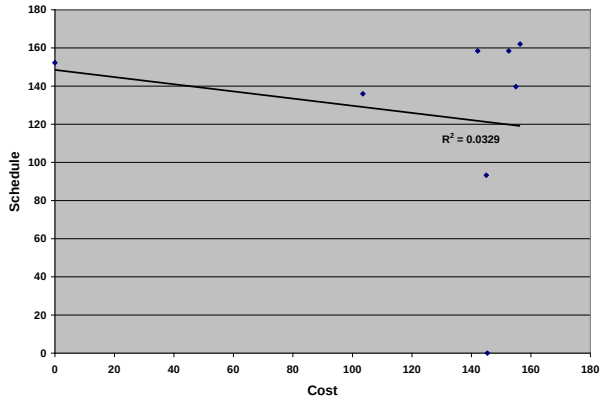


Figure F-1. Cost vs. Schedule

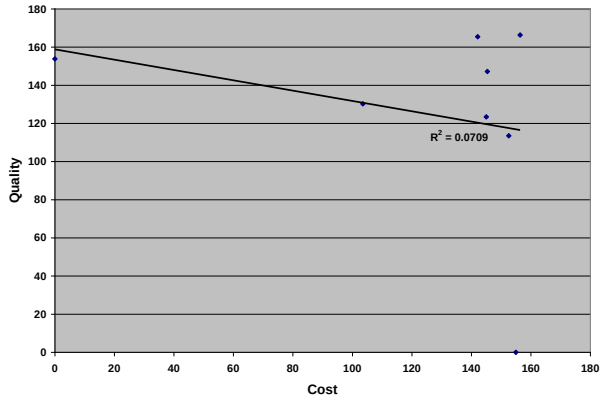


Figure F-2. Cost vs. Quality

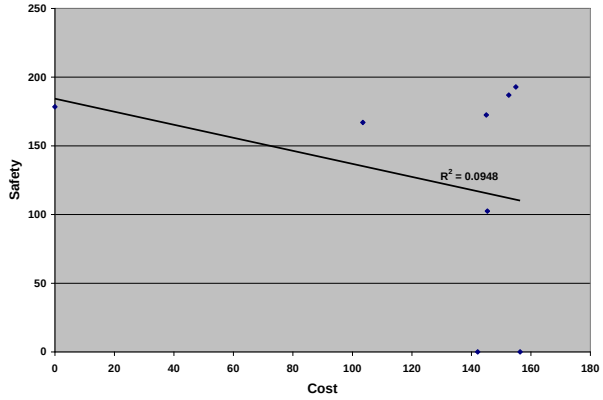


Figure F-3. Cost vs. Safety

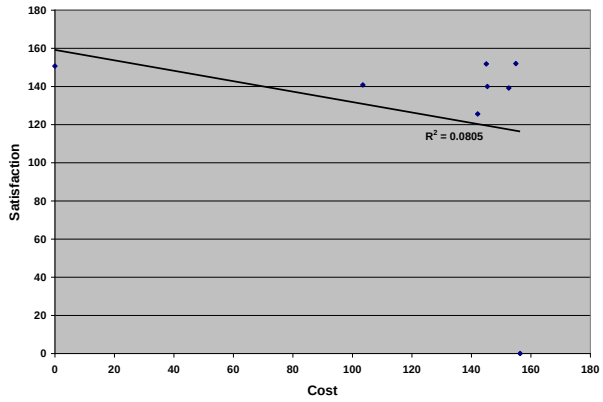


Figure F-4. Cost vs. Satisfaction

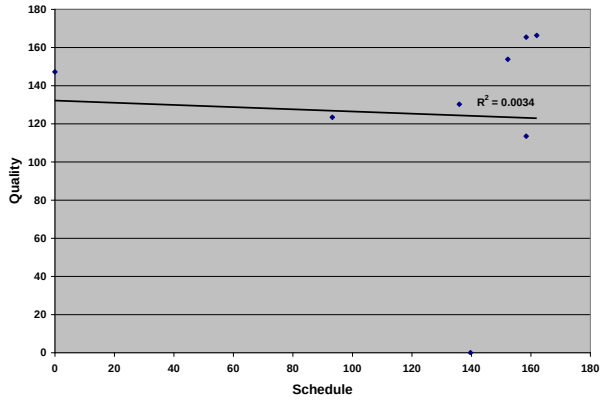


Figure F-5. Schedule vs. Quality

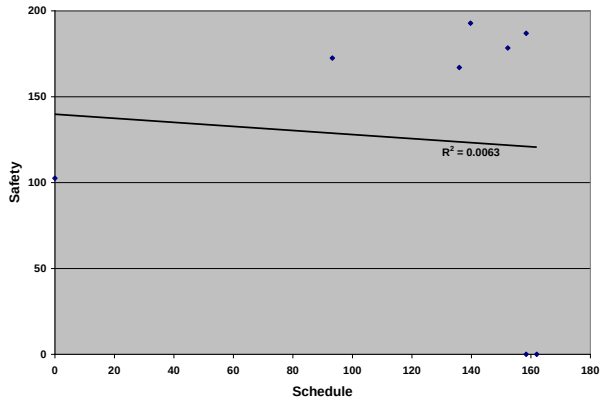


Figure F-6. Schedule vs. Safety

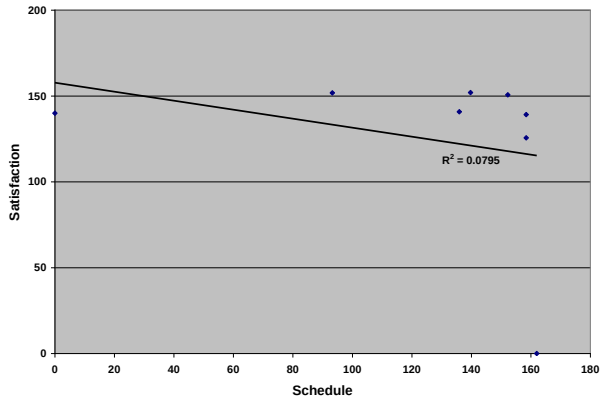


Figure F-7. Schedule vs. Satisfaction

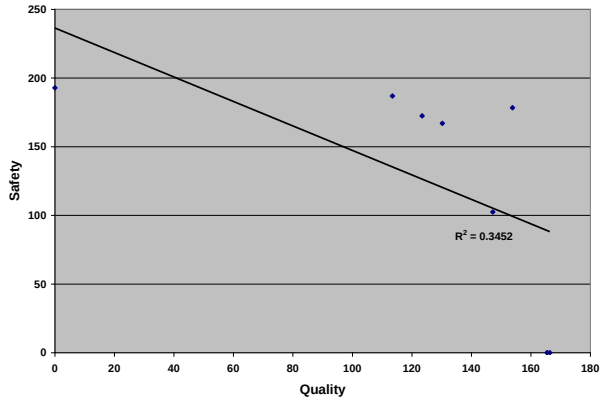


Figure F-8. Quality vs. Safety

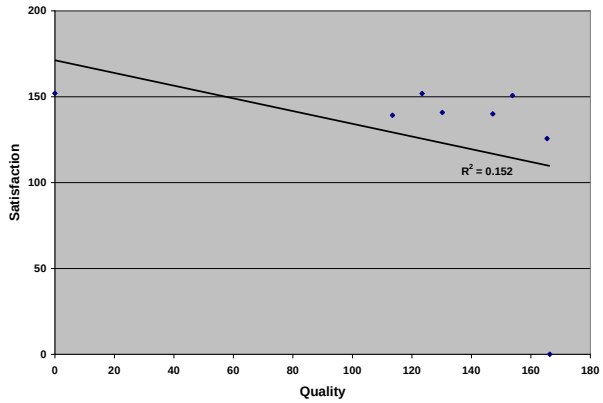


Figure F-9. Quality vs. Satisfaction

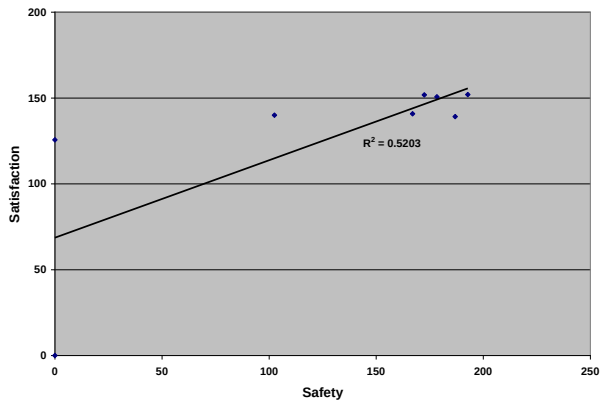


Figure F-10. Safety vs. Satisfaction

APPENDIX G
SURVEY FILE

Survey for Multi-Project Success Parameters and Problems

Overview

1 The purpsoe of this survey is to study multi-project success parameters and project problems.

2 There are more than three (3) project success parameters required to be considered as a successful project. These parameters can come from owner's demands or from your company's strategy (policy).

3 The proposed success parameters included in this survey are:
Cost, Schedule, Quality, Safety, and Owners Satisfaction (Satisfaction).
Please refer to the definition of each success parameter in the sheet of "Success Parameters" if you need clearer definitions of these parameters.

4 Please use only success parameters included in this survey.

5 It is assumed that your company uses a system that classifies the problems its encounters on projects into eight (8) problem groups.
They are Alignment (AL), Constructability (CA), Change Management (CM), Contracting (CO), Project Controls (PC), Quality Management (QM), Safety Practices (SP), and Team Building (TB).
Please refer to the definition of each problem group in the sheet of "Problem Group" if you need clearer definitions of these problem groups.

6 Only complete survey if you have worked on a multi-success parameters project.
A project for this survey is not necessary to be the current project you work for.
You can use one of your past projects for this survey.
For your convenience, present tense is used for survey not past tense.

7 The survey sheet is available in the sheet of "Survey."

8 Please do not hesitate to contact me if you have any question.
You can reach me at (352) 235 - 4111 or thomas16@ufl.edu.
I really thank you for your help.

Figure G-1. Worksheet of instruction

A. Yourself

1 How many years of experience in the construction industry?
Please type your number of experience in the box below.

[ ] years

2 What is your position? (Project Manager, Superintendent)
Please type your position in the box below

[ ]

B. Project

1 What is the name of the project?
Please type the name of the project in the box below.

[ ]

2 Where is the project located? And What year?
Please type the location (City and State) and year in the box below.

[ ]

3 What are the characteristics of the project?
Please mark "x" in the boxes all that apply.

a. Commercial	
b. Hospitalities	
c. Residential	
d. Civil and Heavy	
e. Educations	
f. Government Facilities	
g. Others	

4 When do you join the project?
Please type a number in the box below using multiples of 10 percentages
if the duration from the contract awarded to the substantial completion is 100.
For example,
The number will be zero (0) if you join the project at the time of contract awarded or earlier.
The number will be 30 if you join the project at 30% of the total duration.
The number will be 50 if you join the project at the exact half of the total duration.

[ ] %

C. Multi-Project Success Parameters

1 Select all success parameters that can apply for the project addressed in B. Project.
Min. three (3) and Max. five (5) success parameters are required.
2 Set the priority of project success parameters in 'Priority' table below.
3 Fill in 'Value' in the table below.
The value of highest priority parameter has to be 100.
4 Compare the rest of parameters over the highest priority parameter.
Fill with the highest value first and then lower priority values.
5 Fill in zero (0) value in any parameter
if you do not consider it as a success parameter.
6 You could have multiple same priority and value.
See Safety and Satisfaction in Example.

Figure G-2. Worksheet of survey part A through C

YOUR ANSWER HERE!!! EXAMPLE HERE

Parameter	Priority	Value	Parameter	Priority	Value
Cost			Cost	1	100
Schedule			Schedule	3	85
Quality			Quality	2	90
Safety			Safety	5	72
Satisfaction			Satisfaction	5	72

D. Assessment of Severity of Project Problems

This assessment has to be based on the time you join the project addressed in B. Project.

1 Choose project potential problems.

2 Assess the degree of potential problem severity from your perspective.
The range of severity is in between 0 and 100.
100 is the highest and 0 is the lowest.

3 Fill in the 'Severity' in the table below.

4 Fill in zero (0) value in any problem group
if you do not expect to have any problem with that group.

EXAMPLE HERE

Problem Group	Severity	Problem Group	Severity
AL	80	PC	60
CA	12	QM	70
CM	55	SP	31
CO	40	TB	0

YOUR ANSWER HERE!!!

Problem Group	Severity	Problem Group	Severity
AL		PC	
CA		QM	
CM		SP	
CO		TB	

E. Project Review

1 When do you leave the project addressed in B. Project?
Please type a number in the box below using multiples of 10 percentages
if the duration from the contract awarded to the substantial completion is 100.
For example,
The number will be 90 if you leave the project at 90% of the total duration.
The number will be 100 if you leave the project at the time of substantial completion or later.

[ ] %

2 Are there any changes in success parameters and their priorities before you leave the project?
Fill in the table below as you do in C. Multi-Project Success Parameters if your answer is "Yes."
Skip this question and go to Question 3 if your answer is "No."

YOUR ANSWER HERE!!!

Parameter	Priority	Value
Cost		
Schedule		
Quality		
Safety		
Satisfaction		

Figure G-3. Worksheet of survey part C through E

3 At the time you leave the project and/or while you participate in the project review process, it is assumed that you are told to rank the problem groups from the most critical or serious to the least critical or serious.
This ranking may be your personal opinion or a general consensus if you participate in the project review process.
Please rank eight (8) problem groups from the most to the least critical or serious in the table below.
Type '1' if any problem group is the most critical.
Type '8' if any problem group is the least critical.

EXAMPLE HERE

Problem Group	Ranking	Problem Group	Ranking
AL	6	PC	7
CA	2	QM	3
CM	5	SP	8
CO	1	TB	4

YOUR ANSWER HERE!!!

Problem Group	Ranking	Problem Group	Ranking
AL		PC	
CA		QM	
CM		SP	
CO		TB	

Thank you for your participation. You are done with this survey.

Figure G-4. Worksheet of survey part E

APPENDIX H
REDRAWN REGRESSION MODEL

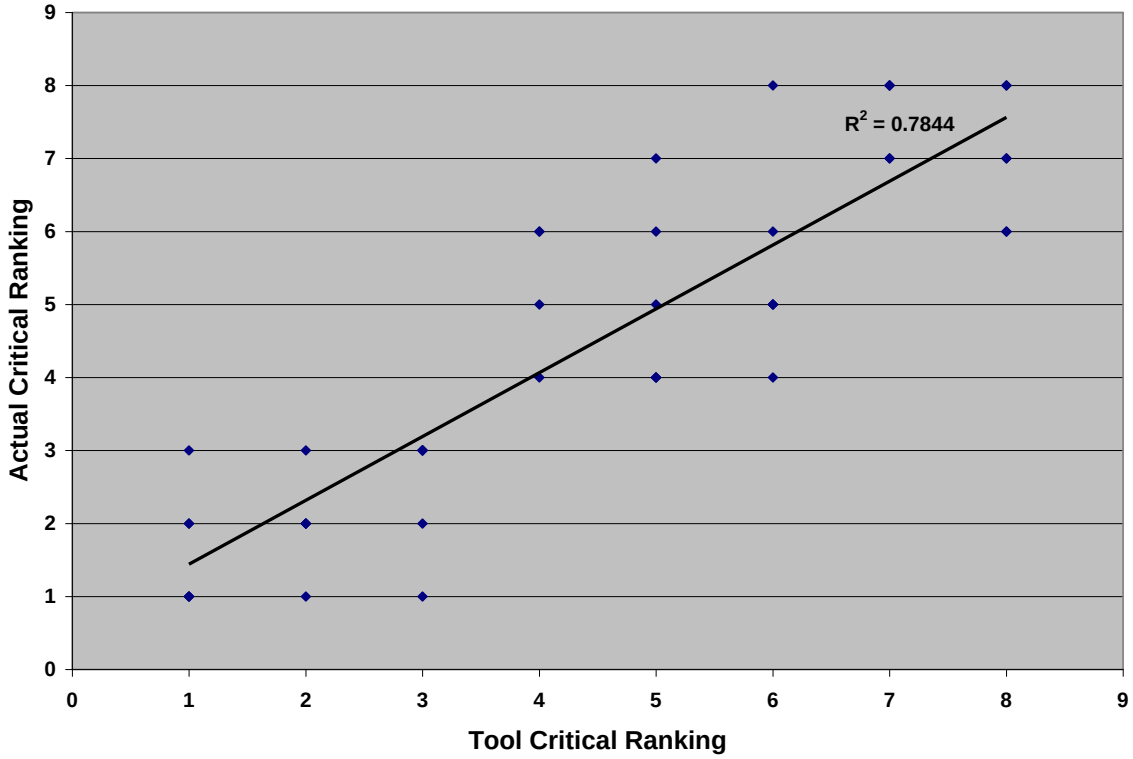


Figure H-1. Redrawn regression model

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BIOGRAPHICAL SKETCH

Seong Jin "Tommy" Kim was born in Seoul, Korea. He has four family members (two parents and two sisters). He grew up in most his time in Koyansi, Kyunggido. The schools he has been to are: Shin Do elementary school, Youn Shin middle school, and Dae Shin high school. Right after he graduated from high school, he went to Soong Sil University for four years of college, majoring in architectural engineering. During the college years, he joined the army for two years as other Korean men do. He loved the design of buildings and houses and won a couple of design competitions during his college years. After graduation he started working with a general contractor for the next five years, three years in Malaysia and two years in Seoul, Korea. When he worked for a general contractor in Korea and Malaysia, he had a chance to meet a lot of people from all over the world and gained experienced in the construction industry. Even though he loved his job and work, he decided to study more to become a better person in the construction industry. After five years of work, he continued studying for his master's degree in civil engineering at Texas A&M University. At that time Tommy decided to be a professor at a university and that is something he would like to do better than anything in the world. When he was done with his master's degree in Texas, he came to the University of Florida to seek his Ph.D in Design, Construction and Planning. His interests in the construction industry are project controls and planning with estimating. His specialties are related to cost and schedule. It has been a long journey to accomplishing his goals but it has still been worth doing. Tommy likes to cook for his friends and families and loves to see movies. He has been a lecturer in the department of construction management at East Carolina University since August 2009.