**Doctor of Philosophy**

# Cost Performance Comparison of Design-Build and Design-Bid-Build Using Moderation and Mediation Effects

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# Abstract

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This research analyzes the cost performance of design-build (DB) and design-bid-build (DBB) delivery systems to examine whether one project delivery system (PDS) is always superior to the other when it presents lower cost growth on average. Previous research has recognized but not yet distinguished between the effects of the PDS and third factors on cost performance and has thus been unable to determine the most significant factor

affecting cost performance of DB projects versus DBB projects. A research model for a causal analysis was proposed, in which this research incorporated influential factors (i.e., project types and bidding characteristics) associated with the cost performance of different PDSs, and categorized these factors. The main concept was to apply causal analysis to the cost performance comparison of DB and DBB. The literature review identified three research categories: (a) comparing project performance of DB and DBB, (b) identifying influential factors that affect project cost performance, and (c) performing association analysis of third factors with PDS in the relationship between PDS and cost performance. This research considers project types to be moderator and bidding characteristics to be mediators and uses an established the research model.

The moderation analysis that examined under what circumstances project types moderate the effect of the PDS on cost performance was conducted prior to the mediation analysis, which determines whether the project type should be controlled when the cost performance of DB and DBB are compared. The mediation analysis explained how bidding characteristics as third factors that tend to increase the project costs during the construction phase and, therefore, mediate the relationship between the PDS and cost performance. The mediation analysis employed a causal relationship model using path analysis to distinguish between the effects of PDS and bidding characteristics on cost performance, and to identify the statistically significant mediation effect of bidding characteristics on cost growth.

Subsequently, a *t*-test was conducted to compare the cost performance of DB and DBB projects by project type and bidding characteristics. Based on public-sector projects in Seoul, South Korea, the results show that DBB architectural building projects have a mediation effect on cost performance; however, this does not hold for civil infrastructure projects. This indicates a condition wherein DB should not be considered superior to DBB despite the lower cost growth on average. Thus, PDSs have the potential to be misjudged when their cost-effectiveness is mediated by bidding characteristics. This research contributes to the construction engineering and management body of knowledge by providing a causal analysis to compare DB and DBB cost performance on the basis of moderation and mediation effects. It presents another dimension of comparison by considering the full life cycle of a project and concludes that DBB is superior in some cases in comparison with DB in terms of cost performance. The findings from this research may provide guidance for practitioners (e.g. public sector owners or architects/engineers (A/E)) when evaluating or selecting a DB delivery system for specific project types, or benchmarking DB against DBB.

**Keywords:** Project Delivery System; Design-Build; Design-Bid-Build; Cost Performance; Cost Growth; Project Type; Bidding Characteristics; Causal Analysis; Moderation Effect; Mediation Effect; Path Analysis

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# Chapter 1

# Introduction

## 1.1 Research Background

In the earliest stage of a research area, attention is focused on establishing evidence of a direct relationship between two variables, X and Y, and demonstrating simple associations or unqualified multivariate associations. However, as the research area develops and matures, focus eventually shifts from demonstrating the existence of an effect toward understanding the mechanism (Hayes 2013). This context also has been presented in the construction management area. As an earlier stage of this area, the analysis of construction project performance based on the project delivery system (PDS) has been conducted using the direct relationship analysis (e.g., comparing the mean value of performance indicators (Y) between PDSs (X)), or association analysis (e.g., correlation, simple multivariate regression analysis with other influential factors).

In recent decades, design-build (DB) delivery systems have been gaining popularity in the architecture/engineering/construction (A/E/C) industry. Comparing DB as an alternative PDS to the traditional design-bid-build (DBB)

has become a subject of significant interest recently (Goftar et al. 2014; Shrestha et al. 2017; Tran et al. 2018). DB is a PDS where the project owner contracts with a single entity to carry out both design and construction under a single contract. DBB is the traditional PDS in many countries where the project owner contracts separately with a designer and a constructor (Konchar and Sanvido 1998; Hale et al. 2009). Most research until the 1990s had concluded that DB is superior to DBB in most aspects (e.g., cost, time, quality, and safety). However, cost performance comparisons since the early 2000s have shown inconsistent results and remain debatable. Some research attributes the inconsistent results to the different project types or datasets considered by the researchers (Asmar et al. 2013; Chen et al. 2016). In addition to the project type issue, this research adds insight into measurement indicators of cost performance in order to understand the mechanism of evaluating PDS.

Project owners mainly use "cost growth[1]" as a cost performance indicator (i.e., performance metric) when evaluating PDSs, specifically to compare DB and DBB. Further, most relevant research has examined the differences in cost

[1] The representation of the term "cost growth" varies depending on the literature. It can be expressed by cost changes, overrun/underrun, deviation, discrepancies, or the variance between initial and final project cost.

growth mean values (i.e., the average rates of cost growth) between DB and DBB using simple linear regression or descriptive statistics, and has concluded that DB outperforms DBB simply because the cost growth for DB is lower than that for DBB on average. Figure 1.1 shows examples of the direct relationship analysis between X (PDS) and Y (cost growth), as well as the trends in the cost performance comparison of PDSs (e.g., DB, DBB, and some projects with construction management at risk (CMR)) compiled from research conducted over the past two decades.

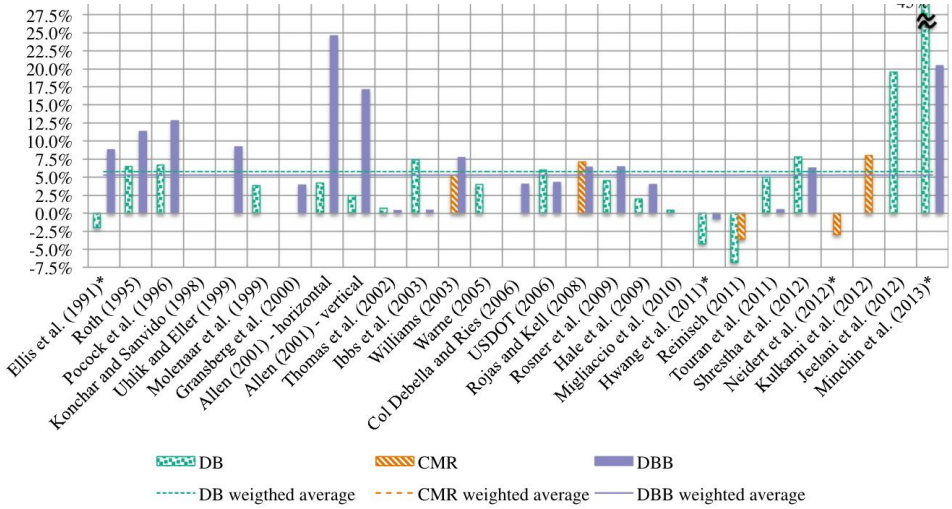



**Figure 1.1** Quantitative literature analysis of cost growth performance for DB, CMR, and DBB delivery systems (* denotes studies using alternative cost growth definitions) (adapted from Sullivan et al. 2017)

From the owners' perspective, lower cost growth is considered superior to a higher one. However, contractors are often in favor of higher cost growth since they use "cost growth" as a means to increase their profitability. DB typically has fewer bidders than DBB, which naturally increases the bid price; moreover, the presence of cost-based competition further lowers the bid price for DBB. If a selected bid price is significantly lower than the owner's pre-bid estimate, then contractors often attempt to preserve or increase their profitability during the construction phase. This type of bidding characteristics—in which the level of competition in a certain PDS affects the bid price—tend to increase project cost because of contractors' strategies.

Based on this mechanism, different PDSs' bidding characteristics affect cost performance. Therefore, it is hypothesized that bidding characteristics have an indirect effect, or mediating role, in the relationship between the PDS and cost performance. In addition, in cases wherein owners evaluate performance, the PDS is assumed to have a direct effect on cost growth. Accordingly, the PDS has causal effects on cost growth that are both direct (from the owners' perspective) and indirect (from the contractors' perspective). Consequently, there are third factors affecting the cost performance comparison of DB and DBB systems: project types and bidding characteristics.

## 1.2 Problem Statements

Answering questions of *how* and *when* provides a deeper understanding of the phenomenon or process under investigation and gives insight into how that understanding can be applied. Analytically, questions of 'how' are typically approached using process or *mediation analysis*, whereas questions of 'when' are most often answered through *moderation analysis* (Hayes 2013).

***Inconsistent results due to differing project types, unspecified or mixed project types used in previous research***

As seen in different trends analyses found in the research and shown in Figure 1.1, researchers consider it to be an outlier if the cost growth of DBB projects is lower than that of DB projects (Goftar et al. 2014; Sullivan et al. 2017). Some research identifies the reason that cost performance comparisons between DB and DBB delivery systems are inconsistent is because of differing project types and datasets (Asmar et al. 2013; Chen et al. 2016). However, these explanations have been somewhat arbitrary and without any theoretical basis. Further, the project types examined by previous research can be unspecified (Ibbs et al. 2003) or mixed types of projects together(Molenaar et al. 1999; Perkins 2009; Chen et al. 2016; Sullivan et al. 2017).

Some research has indicated that the project type moderates (has an influential relationship) other project-related factors' (e.g., knowledge management, bundling policy, project manager's leadership) effects on project performance (Müller and Turner 2007; Yang et al. 2012; Qiao et al. 2019). If the cost growth comparisons vary depending on project type, *the project type could be assumed to moderate the relationship between PDS and cost performance*. Causal analysis could be applied to confirm the role that the project type plays as a moderator.

***Unable to distinguish the effects of PDS and bidding characteristics on cost performance***

If owners do not consider the mediating role of bidding characteristics when evaluating their PDS, then they cannot accurately conclude that DB is always superior to DBB when it presents lower cost growth on average. To be confirmed the misjudgment of this comparison, the contradictory perspectives of owners and contractors on cost growth should be combined and analyzed in a single model. This way can help clarify which of the two influential factors, PDS (direct effect) and bidding characteristics (indirect effect), more significantly affects cost growth. Previous research has attempted to explain third factors (i.e., bidding characteristics) that influence the relationship between the PDS and cost performance. However, the methods used in those research are limited to association or interaction analysis (e.g., correlation and

multiple regression analysis), which cannot separate and identify the effects of PDS and bidding characteristics on cost performance to determine which factor more significantly affects cost growth. To determine the more significant factor, the effects of the PDS (direct effect as well as indirect effect through bidding characteristics) on cost growth should *be distinguished and examined independently* in a single model. To deal with this problem, causal analysis should be utilized.

To address the phenomenon of these inconsistent cost performance results, a causal analysis model that explains the mechanism by which a PDS's effect on cost performance operates differently based on bidding characteristics associated with different project types should be established. As part of the research design, identifying moderators and mediators is necessary to solve complex and unsettled problems in theory development (Xiong et al. 2015). Identifying and quantifying the moderators and mediators are useful to make contributions to the body of knowledge in many situations (Baron and Kenny 1986). Moderation is a causal model that postulates "when" or "for whom" an independent variable most strongly (or weakly) influences a dependent variable, while mediation explains the process of "why" and "how" a cause-and-effect relationship happens (Baron and Kenny 1986; Kraemer 2002; Frazier 2004; Hayes 2013).

## 1.3 Research Objectives and Scope

The goal of this research is to enhance the cost performance comparison of DB and DBB delivery systems using causal analysis. To be achieved this goal, specific objectives are identified as follows:

1) To ascertain whether project types moderate the effect of the PDS on cost performance based on a moderation analysis model.

2) To examine bidding characteristics as mediators affecting the influential relationship between PDS and cost performance using a mediation analysis model.

3) To compare the cost performance of DB and DBB delivery systems based on different moderation and mediation effects.

This research introduces a path analysis (i.e., mediation analysis) that explains the process whereby PDS affects cost performance through different (i.e., direct or indirect) paths, and examines whether either or both of the two factors, PDS and bidding characteristics, has a statistically significant effect on cost performance. Prior to the mediation analysis, the project type was examined whether it is identified as a moderator using both the statistical and

data mining methods. The results of the moderation analysis helped select the proper project type for the mediation analysis. Based on the moderation and mediation model results, this research conducted a t-test to compare the cost performances of DB and DBB delivery systems. The methods for these analyses are introduced in Chapter 3.

A database of public-sector projects in Seoul, South Korea was used to conduct this research. The results are expected to provide insights into how to approach the cost performance comparison of DB and DBB, taking into account project types, for public-sector owners and A/E.

The main scope of this research was DB and DBB delivery systems, specifically regarding the cost performance analysis of different PDSs. Numerous studies that evaluate PDSs in terms of cost performance have been conducted by comparing two prevalent PDSs: DB and DBB (Bennet et al. 1996; Konchar and Sanvido 1998; Molenaar et al. 1999; Ibbs et al. 2003; Minchin et al. 2013). Given the inconsistent cost performance results in the comparison of DB and DBB delivery systems and the fact that these PDSs are widely used around the world, this research worked to determine the reasons for these inconsistencies. The procurement and construction phases of the project life cycle in which the PDS selection, bidding, and cost growth occur were targeted. The owner type focused on in this study was the public sector, meaning large

projects executed in a mega-city. The cost was defined as the design and construction cost of the base project. It did not include land acquisition, extensive site work, process, or owner costs. Cost indicators as part of various aspects of the PDS performance (e.g., time, quality, safety, productivity, etc.) was carefully analyzed, as this was the main focus of the study. Project owners' pre-bid estimations by engineers were assumed to be appropriately estimated because most public sector projects have accumulated enough similar samples off of which to base them. The terminology used in different project types varied depending on the literature, such as project characteristics, remodeling or new construction, facility type, and so forth. This research defined the project type as a kind of facility (e.g., building, civil infrastructure, road, and so on).

## 1.4 Dissertation Outline

This research utilized causal analysis of moderation and mediation effects to enhance cost performance comparisons of DB and DBB delivery systems. To address the difficulties of applying the causal relationship model, this research aimed to develop approaches that distinguished and quantified the effects of the PDS on cost performance. Figure 1.2 describes the process this research took to achieve the research objectives. This dissertation began with an introduction describing the importance of analyzing the effects of the PDS on cost performance for research purposes. After explaining the challenging issues of causal analysis in evaluating cost performance, the research goals, specified objectives, and research scopes were explained.

In Chapter 2 (Preliminary Research), the literature from previous research in this area was reviewed, compared, and analyzed. The review results informed the research problem statements discussed in the introduction. Theories and concepts were utilized to design a research model for the comparison of DB and DBB and to establish the hypotheses.

In Chapter 3 (Research Methodology), the research methods were introduced that were used to validate and verify the moderation and mediation

effects found in the causal analysis. Based on the proposed research model in the previous chapter, the research model framework was divided into five stages. The major methods were path analysis from a structural equation model, a two-way ANOVA, ensemble learning, and a *t*-test.

Chapter 4 (Moderation Model) describes the process for developing, validating, and verifying the moderation effect analysis model for testing whether the project types moderate the effect of PDS on cost performance (Hypothesis 1). In the moderation model development section, a conceptual and statistical moderation model was established. Data collection and analysis were used to explore various attributes, and descriptive statistics of variables were calculated. To validate and verify the moderation model, the interaction analysis of project type, and visualizing the moderation effect, multi-group analysis, and ensemble-stacking learning were performed.

Chapter 5 (Mediation Model) explains the development and validation of a mediation effect analysis model that tested the causal relationship between the PDS and cost performance using a path analysis method (Hypothesis 2). In the mediation model development section, the model framework is established, and the variables and theoretical path model are defined. In the model validation section, the effects of PDS on cost performance are identified and quantified through the three experimental steps.

In Chapter 6 (Comparing Cost Performance of DB and DBB), the comparison of the cost performance of DB and DBB delivery systems using moderation and mediation effects are described. This chapter analyzed the cost performance of PDSs, reflecting the full life cycle of a construction project based on the third factor between PDS and cost performance (i.e., project type, bidding characteristics). At the end of the chapter, practical applications are discussed.

Chapter 7 (Conclusions) provides an overall summary of this research's results, expected contributions to the body of knowledge in the field of construction project delivery management, limitations of this research, and possible future research to address the research limitations.

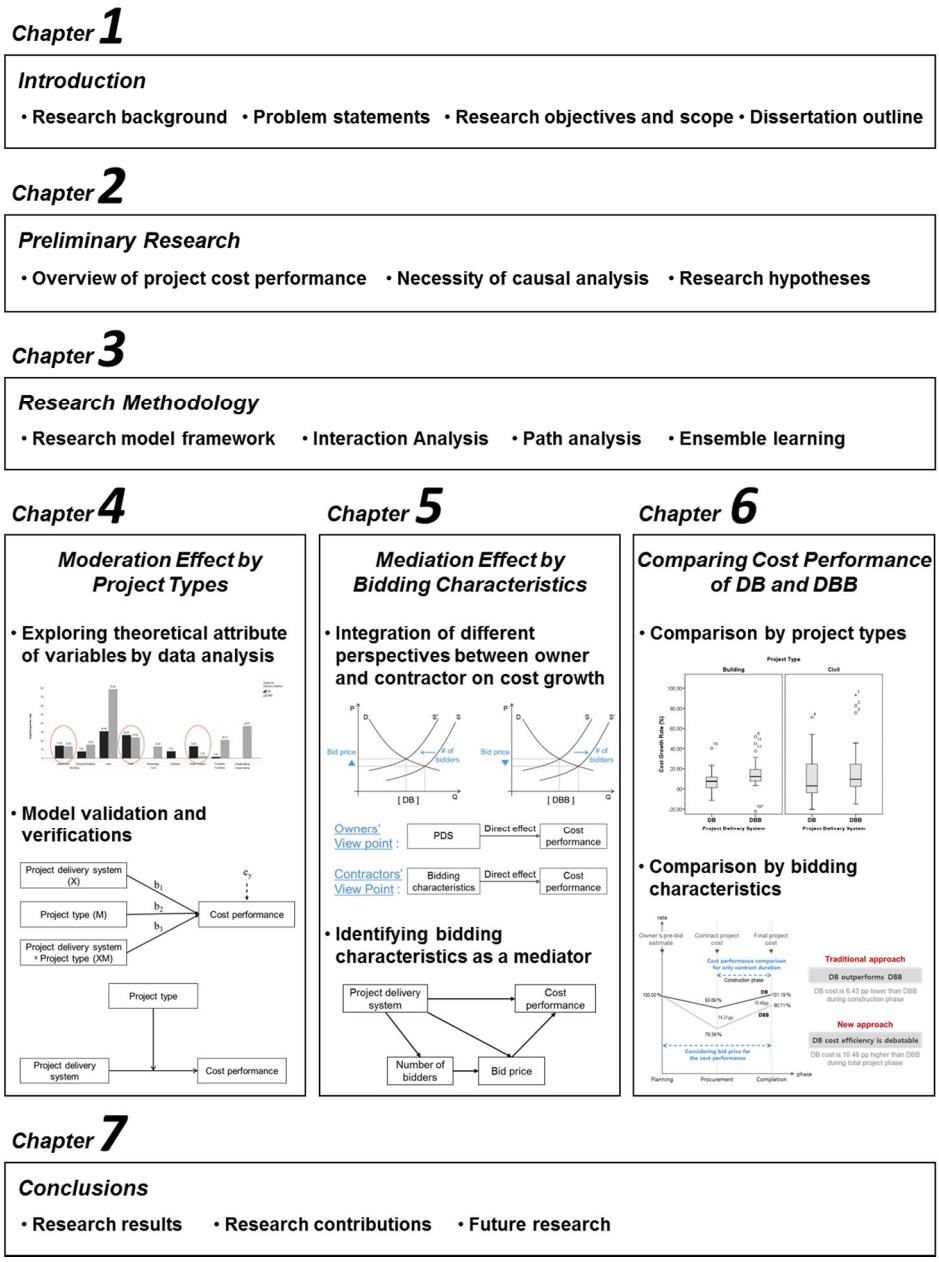



**Figure 1.2** Dissertation outline

# Chapter 2

# Preliminary Research

This chapter explains the necessity of causal analysis for the cost performance comparison of DB and DBB delivery systems. It gives an overview of project cost performance studies that have been conducted according to the literature review, and how third factors (i.e., bidding characteristics, project type) have been treated as mediation and moderation effects on the causal relationship between PDSs and cost performance. Finally, the research model and research hypotheses were established.

## 2.1 Overview of Construction Project Cost Performance

### 2.1.1 Project Owners' Perspective on Cost Performance

From a project owners' viewpoint, the cost performance evaluation is a prerequisite for choosing the PDS that will execute a project within budget. DB and DBB delivery systems are used worldwide and have been analyzed and compared in numerous research. Until the 1990s, most research on the topic had concluded that DB outperforms the traditional DBB delivery system in most aspects (e.g., cost, time, quality, and safety) (Bennett et al. 1996; Songer

and Molenaar 1996; Konchar and Sanvido 1998; Molenaar et al. 1999). Accordingly, the research tends to advocate for DB as an alternative delivery system to the traditional DBB system. However, since the early 2000s, relevant research has shown contradictory results in terms of cost performance comparisons of the two delivery systems (Thomas et al. 2002; Ibbs et al. 2003; Federal Highway Administration 2006; Korkmaz et al. 2010; Fernane 2011; Minchin et al. 2013; Chen et al. 2016; Shrestha and Fernane 2017).

A National Institute of Standards and Technology study conducted by the Construction Industry Institute (CII) (Thomas et al. 2002) analyzed a large database of projects. The database distinguished between projects submitted by owners from projects submitted by contractors, and the cost performance between DB and DBB differed according to the project stakeholders. Ibbs et al. (2003) studied DB and DBB using data from the CII projects and found that DB outperformed DBB in terms of schedule performance, but the results for cost and productivity performance were the inverse. In 2006, the Federal Highway Administration in the United States compared the project performance of DB highway projects with similar DBB highway projects (USDOT 2006). The study results showed that the DB projects had higher cost increases but lower schedule growth than the DBB projects.

A recent review of the literature on this topic showed that performance results are mixed depending on the project characteristics and other factors specific to the individual project. When sustainable high-performance buildings are studied, the level of integration in the delivery process provided by different delivery methods should be considered. Korkmaz et al. (2010) indicated that overall, CMR and DB are superior to DBB projects. Minchin et al. (2013), who focused on transportation project contract types, showed that DB projects result in improvements in schedule performance, whereas the cost savings are lower than with DBB projects. A recent study by Chen et al. (2016) explored the relationship of project characteristics with performance levels, such as project type, owners (public/private), procurement methods, contract methods, and Leadership in Energy and Environmental Design levels. This study used a large sample of building projects from the Design Build Institute, a US-based database. The results showed that whether DB has an advantage in terms of cost savings remains uncertain.

Research has been relatively consistent that DB is superior to DBB in terms of project schedule, but results on the cost-effectiveness of DB remain debatable. Some research attributes the inconsistent results to the different project types or datasets considered by the researchers (Asmar et al. 2013; Chen et al. 2016).

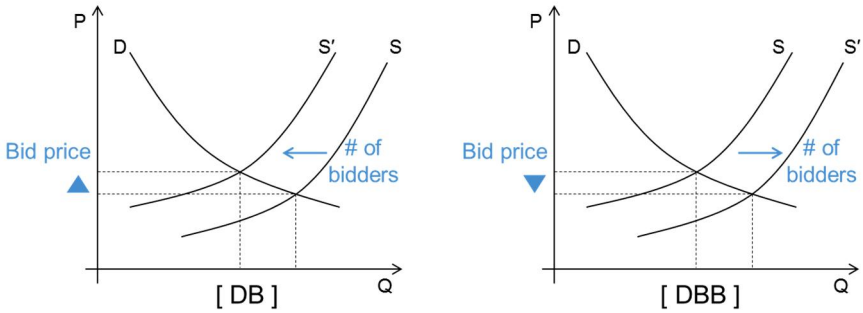
To compare the cost performance of DB and DBB, most relevant research has tested statistical mean differences of cost growth (i.e., the average difference in cost growth rates) between DB and DBB projects, concluding that the DB system is considered superior when its mean value of cost growth presents lower than that for DBB system. Previous research comparing DB and DBB performance is assumed to approach the issue from the owners' perspective since project owners select a PDS based on their performance evaluations of similar earlier projects and project owners prefer lower cost growth.

### 2.1.2 Contractors' Perspective on Cost Performance

Contrary to the owners' perspective, contractors are often in favor of higher cost growth. According to previous research, the level of competition (i.e., number of bidders) affects the awarded bid price, which tends to generate higher cost growth during the construction phase when the bid price is significantly lower.

Rosmond (1984) found that an increase in competition intensity (i.e., the number of bidders) results in an excessive use of change orders (i.e., cost growth). Further, Jahren and Ashe (1990) identified four primary factors that influence cost growth: project size, bid price to estimate ratio, project type, and

the level of competition. Williams (2005) studied the nature of the bid ratio, indicating the pattern of submitted bids that is associated with increased final project cost. Specifically, the research postulated that when the low bid is much lower than the other bids, a bidder will recoup losses by increasing the project cost. In another study, Kuprenas (2005) used regression analysis and found that bidding characteristics, including bid price and the number of bidders, are correlated with construction cost performance. This issue reflects the contractors' strategies that tend to preserve or increase their profit according to free-market economic theory as shown in Figure 2.1.




Note: P = price; Q = quantity; D = demand; S = supply

**Figure 2.1** Contractors' strategy according to economic free-market theory

Further, Gkritza and Labi (2008) identified the following intermediate factors that affect cost discrepancies (e.g., cost overruns, and underruns): award amount, number of bidders, and contract period. They considered bidding characteristics to be intermediate factors in the relationship between root

causes (e.g., design errors, unexpected site conditions, and project type) and cost discrepancies. The research implies that bidding characteristics operate as third factors that influence the relationship between PDS and cost performance and should be examined when the cost performance of a PDS is analyzed.

### 2.1.3 Cost Performance Metrics

Since cost performance metrics are varied, the cost performance metric for this research needed to be determined. In the UK, Key Performance Indicators (KPI) are utilized for performance evaluation. KPI addresses cost, time, quality, change orders, rework, safety, etc. In the US, the CII and National Construction Goals evaluate the performance of PDSs. The CII has been developing a project performance database by operating a performance evaluation system called Benchmarking & Metrics since 1996. This database is utilized in much research in order to compare the performance of DB and DBB systems.

Various performance metrics for cost are used to measure the performance of PDSs. Several key metrics are 1) unit cost, 2) cost growth, and 3) intensity (cost/time) (Konchar and Sanvido 1998; Ling et al. 2004; EI Wardani et al. 2006; Asmar et al. 2013).

1) Cost Growth

Cost growth is the difference between contract amount and completion amount. It is widely used as a cost performance metric. In some research, the terms vary: cost changes, overrun/underrun, variance, escalation, deviation, discrepancies between initial and final contract amount.

Cost Growth (%) (Eq. 2.1)

$$= \frac{\text{Final project cost} - \text{Contract project cost}}{Contract\ project\ cost} \times 100$$

2) Unit Cost

Unit Cost is the dollars spent per square meter.

$$\text{Unit Cost (\$/m}^2\text{)} = \frac{\text{Final project cost}}{Area} \div Index \quad \text{(Eq. 2.2)}$$

3) Intensity

As a hybrid of cost and schedule measures, intensity is the unit cost of design and construction work put in place in a facility per unit time.

$$\text{Intensity [(\$/m}^2\text{)/month]} = \frac{\text{Unit cost}}{Total\ time} \quad \text{(Eq. 2.3)}$$

Equations 2.1-2.3 are major performance metrics for project cost analysis. Among those metrics, cost growth (the difference between initial and completion amounts) is the most widely used cost performance metric. Besides,

this research selected “cost growth” as a performance measurement indicator because the cost growth issue is getting complicated and should be discussed to improve evaluation of cost performance of a PDS. Shrestha et al. (2017) defined the detailed metrics that focus on cost growth as follows.

Contract award cost growth (%) (Eq. 2.4)

$$= \frac{\text{Contract design and construction cost} - \text{Estimated design and construction cost}}{\textit{Estimated design and construction cost}} \times 100$$

Design and construction cost growth (%) (Eq. 2.5)

$$= \frac{\text{Final design and construction cost} - \text{Contract design and construction cost}}{\textit{Contract design and construction cost}} \times 100$$

Total cost growth (%) (Eq. 2.6)

$$= \frac{\text{Final design and construction cost} - \text{Estimated design and construction cost}}{\textit{Estimated design and construction cost}} \times 100$$

The calculation of cost growth can be defined as any of Equations 2.4-2.6 due to a lack of standard terminology. Some previous research confuses the term, for example, the initial amount used in previous research could be both the owner’s pre-bid estimation or contract amount. This research also utilizes various dimensions of cost growth according to the project life cycle.

## 2.2 Necessity of Causal Analysis

### 2.2.1 Third Factors (Project Type and Bidding Characteristics) Affecting the Cost Performance Comparison of DB and DBB

Previous research has attempted to identify the causes of the inconsistency in cost performance comparisons of DB and DBB delivery systems, mainly using association analyses among influential cost growth factors (Ling et al. 2004; Korkmaz et al. 2010, 2013; Shrestha et al. 2012). Konchar and Sanvido (1998) mentioned that some of their study results cannot be explained because causal factors were not measured by the study. Some research stated the need for causal analysis in order to better understand different PDS's performance (Chen et al. 2016; Shrestha et al. 2017). However, the causal analysis of this comparison using empirical data has not been conducted. Exploring the moderation and mediation roles of third factors (i.e., project type and bidding characteristics) is the first step in a causal analysis of the cost performance of different PDSs.

As mentioned in the research background section, "project type" is one of the major factors that seem to be leading to discrepancies in cost performance comparisons of DB and DBB delivery systems. A number of studies indicate that project type affects cost performance (Jahren and Ashe 1990; Konchar and

Sanvido 1998; Love 2002; Gkritza and Labi 2008; Asmar et al. 2013; Chen et al. 2016; Liu et al. 2016). Some other research shows that the project type affects (i.e., moderates) the relationship between a PDS and cost performance, or between other influential factors and cost performance (Müller and Turner 2007; Yang et al. 2012; Qiao et al. 2019).

Some research compared DB and DBB systems based on third factors (i.e., bidding characteristics). For instance, Ling et al. (2004) studied 87 building projects in Singapore using interactive analysis and concluded that the cost growth for both DB and DBB is higher when contractors with a low amount of paid-up capital are engaged. EI Wardani et al. (2006) compared project performance to the procurement method utilized for 76 DB projects in the United States. According to them, even in the DB system, projects procured on low bids experienced the highest cost growth due to change orders, indicating that this result is affected by the level of competition and bid price (i.e., bidding characteristics). Further, Fernane (2011) stated that DBB results in higher cost growth than DB due to the former's bidding characteristics and the owner's design responsibility (e.g., design errors, omissions). Chen et al. (2016) found that the time and cost performances of DB projects are affected by procurement methods, owner types, and contract methods.

### 2.2.2 Limitations of Previous Research

Table 2.1 depicts the findings of 20 research comparing the cost growth of DB and DBB projects, organized by project type in chronological order. The project types included building projects (9 studies), civil projects (6 studies), and mixed building and civil projects (5 studies).

Most of the studies specify the project type (e.g., architectural building, highway, road, water sewage, bridge, etc.) when they compare DB and DBB systems. However, some research conducted the comparison without considering the project type, only mentioning some project characteristics such as whether they were large and complex projects (Ibbs et al. 2003). Further, some other research integrated or mixed the project types due to the insufficient number of samples (Molenaar et al. 1999; Perkins 2009; Chen et al. 2016; Sullivan et al. 2017). Odeck (2004) found that neither project type nor work force type seems to influence the level of cost overrun, which is the opposite result found in most other research.

**Table 2.1** Findings of 20 research on project type, cost growth, and methods in the comparison between DB and DBB

| Researchers | Project type (level 2) | PDS | Sample size | Findings in cost growth | Third factor analysis | Methods |
|---|---|---|---|---|---|---|
| | Building (9 studies) | | | | | |
| Roth (1995) | Navy child care facilities | DB<br>DBB | 6<br>6 | Cost growth for DB was lower than that for DBB (not significant). | - | *t*-test |
| Pocock et al. (1996) | 12 different military facility types | DB<br>DBB | 5<br>7 | Cost growth for DB was 6.15% lower than that for DBB. | Interaction | *t*-test + interaction analysis |
| Konchar and Sanvido (1998) | General buildings (6 types) | DB<br>DBB | 155<br>116 | Cost growth was less in DB for high-technology buildings.<br>Cost growth for DB was 5.2% lower than that for DBB. | Interaction | Univariate analysis, multivariate linear regression |
| Ling et al. (2004) | Residential building, factory, office, school | DB<br>DBB | 33<br>54 | Cost growth for DB and DBB would be higher if contractors with lower paid-up capital are engaged. | Interaction | Statistical relationship/ multivariate linear regression |
| Hale et al. (2009) | Navy bachelor enlisted quarters | DB<br>DBB | 38<br>39 | Cost growth for DB was 2.0% lower than that for DBB. | - | ANOVA |
| Korkmaz et al. (2010) | Green office building | DB<br>DBB | 8<br>13 | Cost growth for DB was higher than that for DBB (contractor's involvement at the design stage was higher). | Association (regression analysis) | Mean difference +covariance/ ANCOVA |
| Fernane (2011) | Public university | DB<br>DBB | 42<br>42 | Construction cost growth for DB was 5.4% higher than that for DBB (not significant). | - | ANOVA, t-test |

| Researchers | Project type (level 2) | PDS | Sample size | Findings in cost growth | Third factor analysis | Methods |
|---|---|---|---|---|---|---|
| Korkmaz et al. (2013) | Green building | DB<br>DBB | 4<br>3 | Cost growth for DB was lower than that for DBB | Interaction | Descriptive statistics |
| Shrestha and Fernane (2017) | Public university | DB<br>DBB | 38<br>39 | Design and construction cost growth for DB was 5.1% higher than that for DBB (not significant). | - | ANOVA |
| | Civil (6 studies) | | | | | |
| Warne (2005) | Highway | DB<br>DBB | 21<br>N/A | DB offered greater price certainty and reduced cost growth than DBB. | - | Descriptive statistics |
| FHwA (2006) | Highway | DB<br>DBB | 11<br>11 | Cost growth for DB was 3.8% higher than that for DBB. | - | Descriptive statistics |
| Shrestha et al. (2007) | Highway | DB<br>DBB | 4<br>11 | Cost growth for DB was 9.59% lower than that for DBB. | - | ANOVA |
| Shrestha et al. (2012) | Highway | DB<br>DBB | 6<br>16 | Cost growth for DB was 1.5% lower than that for DBB (not significant, p=.751). | Association | ANOVA, t-test, correlation |
| Minchin et al. (2013) | Highway, bridge | DB<br>DBB | 30<br>30 | Cost saving (cost growth) of DBB is the same or better than DB. | - | ANOVA, t-test |
| Tran et al. (2018) | Highway (5 work types) | DB<br>DBB | 139<br>139 | Cost growth for DB in miscellaneous highway work was 3.61% lower than that for DBB. For other work types as well, DB has lower cost growth, but it is not significant. | - | t-test |

| Researchers | Project type (level 2) | PDS | Sample size | Findings in cost growth | Third factor analysis | Methods |
|---|---|---|---|---|---|---|
| | Mixed (5 studies) | | | | | |
| Molenaar et al. (1999) | Building, industrial, heavy and highway, environmental | DB<br>DBB | 104<br>N/A | Among DB projects, 59% used 2% or more of the established budget. | - | Descriptive statistics |
| Ibbs et al. (2003) | Large and complex projects from CII | DB<br>DBB | 24<br>30 | Relative cost change for DB was 7.8% higher than that for DBB. | - | Descriptive statistics |
| Perkins (2009) | U.S. army base/ various buildings, road, paving | DB<br>DBB | 14<br>20 | Construction cost growth for DB was 3.5% lower than that for DBB. | - | t-test |
| Chen et al. (2016) | Commercial/institutional building, civil infrastructure, industrial facilities | DB<br>DBB | 418<br>N/A | Cost overrun varies between owner type and contract methods. uncertain | Interaction | ANOVA |
| Sullivan et al. (2017) | All types | DB<br>DBB | 30 studies | Cost growth for DB was 2.3% lower than that for DBB. | - | t-test |

Note: PDS = project delivery system; DB = design-build; DBB = design-bid-build; N/A = non-applicable or unavailable information; ANOVA = analysis of variance; ANCOVA = analysis of covariance; FHwA = Federal Highway Administration; CII = Construction Industry Institute

Among the 20 research, 7 reported contradictory results on whether DBB projects have lower cost growth than DB projects. Further, 6 of the 20 research considered factors influencing cost performance and conducted correlation or regression analyses examining the association relationship between variables. However, these studies only examined the direct effects of independent variables on dependent variables; none of them considered a causal analysis to examine indirect (i.e., intervening or mediating, moderating) effects between variables.

The previously mentioned research explains that bidding characteristics influence the relationship between different PDSs and cost performance; however, the methods applied to evaluate that influence has been limited to multiple regression analysis, which analyzes only the direct relationship between independent and dependent variables (i.e., PDS and cost growth in this case), and the associational relationship between independent variables (i.e., PDS and bidding characteristics).

To date, causal analysis has not been conducted to validate the indirect relationship between the independent and dependent variables in the cost performance research area. There are three common types of causal hypotheses: direct causal effect, moderated causal effect, and mediated causal effect (Wegener and Fabrigar 2000; Wu and Zumbo 2008). Figure 2.2 describes the

research stages which address causal relationships between variables. The first and the second analyses from the left side of the figure have generally been covered by previous research in this area, which has conducted direct causal effect analysis (i.e., simple multiple regression, and associations) as the earliest stage of the research area.

However, the research questions have become more complicated and nuanced (Hayes 2013; 2018). Research in this area needs to explain "how" these phenomena occur, as well as "when", "under what conditions", and "for whom." Accordingly, indirect relationship analyses addressing processes or mechanisms are necessary to advance to the matured stage of this research area.

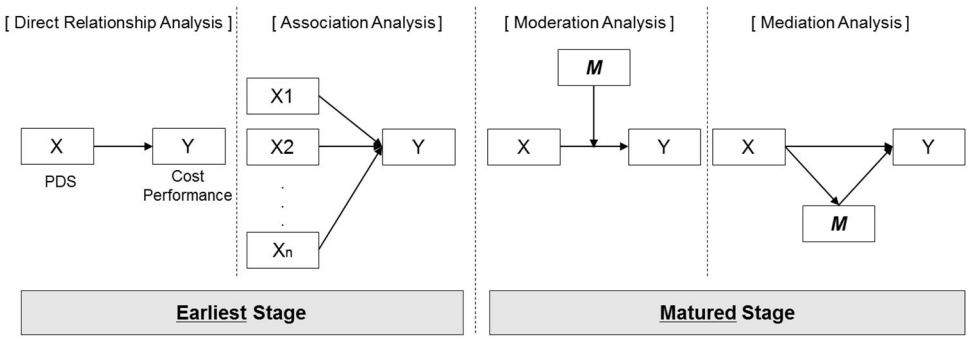



**Figure 2.2** Necessity of causal analysis in cost performance evaluation research area

### 2.2.3 Proposed Causal Relationship Model (Research Model)

According to previous efforts analyzing project cost performance described in Sections 2.1 and 2.2, three types of research on cost performance were defined:

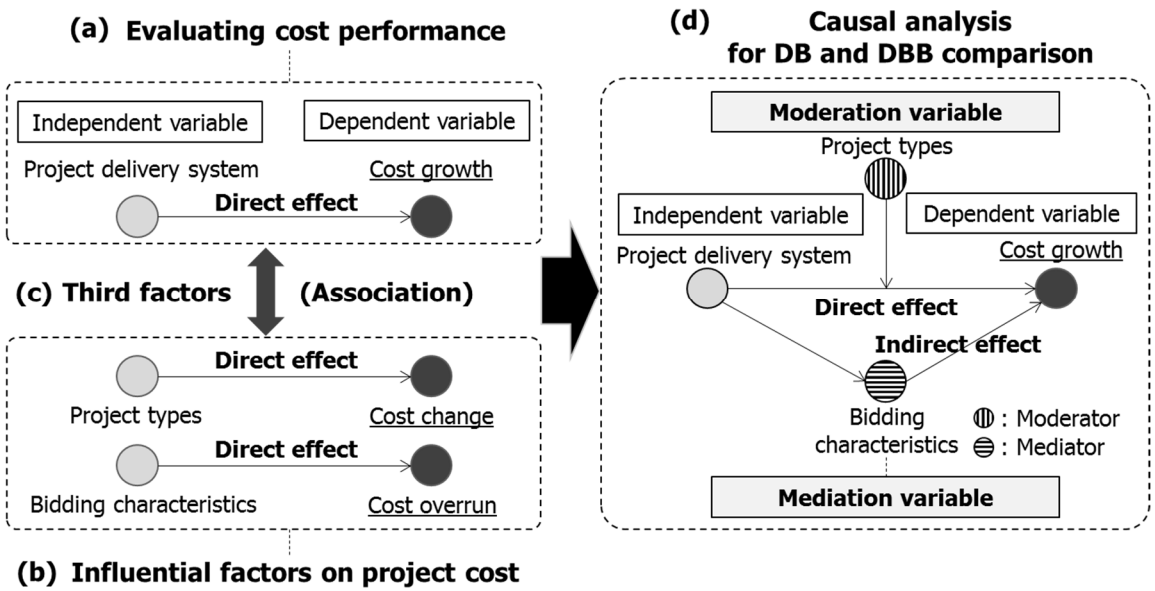
(a) comparing project performance of DB and DBB, as well as, evaluating cost growth from the owners' perspective (Figure 2.3(a)).

(b) identifying influential factors affecting project cost performance from the contractors' perspective (Figure 2.3(b)).

(c) associational analysis of third factors in the relationship between different PDSs and cost performance (Figure 2.3(c)).

In addition, Figure 2.3(a,b,c) illustrates a framework of how previous research has compared DB and DBB, categorized by project type and bidding characteristics.

Consequently, the selected factors for this research were PDSs in the form of DB and DBB delivery systems, the number of bidders and bid price at the bidding stage (which together represent bidding characteristics), project type, and cost growth as a cost performance metric (which is commonly used in research conducted from both the owners' and contractors' perspectives). These factors were postulated in a single, causal analysis model (Figure 2.3(d)).




Note: DB = design-build; DBB = design-bid-build. References of (a) are listed in Table 2-1; references of (b) are Rosmond 1984, Jahren and Ashe 1990, Williams 2005, Kuprenas 2005, Gkritza and Labi 2008; and references of (c) are Ling et al. 2004, EI Wardani et al. 2006, Fernane 2011, Chen et al. 2016.

**Figure 2.3** Different types of research on cost growth (a, b, c) and a causal relationship model for the current research (d)

Based on the findings of previous research, this research seeks to provide new insights into the comparison of DB and DBB by examining the causal factors that moderate and mediate the relationship between PDSs and their cost growth. A causal analysis model was necessary to develop in order to simultaneously consider the perspectives of both owners and contractors by project types.

## 2.3 Research Hypotheses

To be applied causal analysis to the cost performance comparison of DB and DBB delivery systems, two research hypotheses were established based on the literature review and the proposed causal relationship research model.

***Hypothesis 1: Project types moderate the effect of the PDS on cost performance.***

Project types have been one of the main reasons identified as the cause of inconsistent comparisons between DB and DBB cost performance. Previous research shows that cost performances have varied depending on project types. The research can be specific and nuanced, but also at times mixed or without enough information. This research carefully examines whether the project

types influence the effect of a PDS on cost performance. Hypothesis 1 provided a theoretical foundation for Hypothesis 2.

***Hypothesis 2: Bidding characteristics exhibit an indirect (i.e., mediating) effect on the relationship between PDS and cost performance.***

Previous research has studied influential relationships not only of the PDS on cost performance but also of the bidding characteristics on cost performance. However, any prior research that examines bidding characteristics as an intervening factor between the PDS and cost performance has not been aware. Given the effect of the PDS on bidding characteristics (EI Wardani et al. 2006; Fernane 2011), the effects of bidding characteristics on cost performance merit consideration. Additionally, when the level of competition in low-bid procured projects is higher, bidding characteristics are more likely to affect cost performance. In this case, bidding characteristics were hypothesized to mediate the effects of the PDS on cost performance.

## 2.4 Summary

The main purpose of this chapter was to establish a research model and research hypotheses based on the literature review. In the first section, an overview of project cost performance was provided related to PDS and bidding characteristics. Cost performance metrics for this research were selected based on the literature review. Two relevant perspectives from project owners and contractors were identified in the comparison between DB and DBB cost performance. In previous research, project types used for PDS performance analysis have sometimes been unspecified or even mixed due to a lack of data. The project types were identified as moderators between project characteristics and project performance in previous research. These factors supported the necessity for a causal analysis of the cost performance comparison of DB and DBB delivery systems.

Based on the influential factors (i.e., project types and bidding characteristics) associated with PDS and cost performance that were reviewed and categorized into third factors, a research model for the causal analysis was proposed. The literature identified three kinds of research categories: (a) comparing project performance using different PDSs, (b) influential factors affecting cost performance of projects using different PDSs, and (c) association

third factors with the effect of different PDSs on cost performance. This research considered project types as moderators and bidding characteristics as mediators, and used an established research model.

Following the proposed research model, the research hypotheses were defined as such: Hypothesis 1 was that the project type moderates the effect of the PDS on cost performance, and Hypothesis 2 was that bidding characteristics exhibit a mediating effect on the relationship between PDS and cost performance.

# Chapter 3

## Research Methodology

This chapter introduces the research methods used to validate and verify the moderation and mediation effects found in the causal analysis. Based on the proposed research model in the previous chapter, the research model framework was developed and divided into five stages, as described in Figure 3.1. The major methods were path analysis from a structural equation model, a two-way ANOVA, ensemble learning, and a *t*-test.

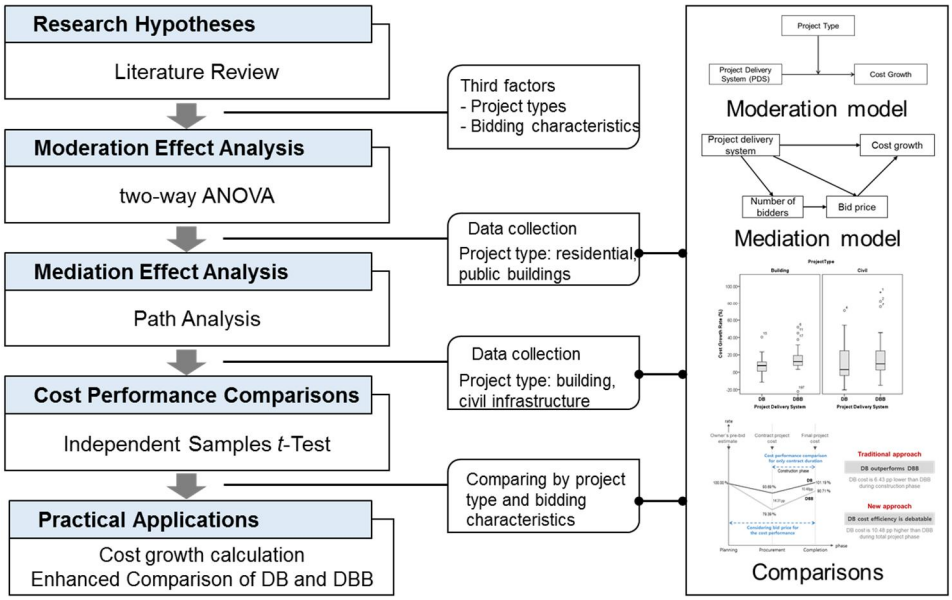



**Figure 3.1** Research model framework

## 3.1 Analysis of Variance for Moderation Model

A moderator is defined as a third variable that modifies a causal effect (Wu and Zumbo 2008). An association between two variables X and Y is said to be moderated when its size (strength) or sign (direction) depends on a third variable (Baron and Kenny 1986; Wu and Zumbo 2008; Heyes 2013). More specifically, the effect of an independent variable on the dependent variable differs depending on the value of a third variable, called the moderator (Jaccard and Turrisi 2003). The moderation effect is typically examined by testing for interaction between the moderator and X in a model of Y (Heyes 2013).

When the question motivating the research asks "when" or "under what circumstances" X exerts an effect on Y, moderation analysis is an appropriate analytical strategy (Hayes 2013). Measuring the moderation effect uses a causal model that postulates "when" or "for whom" an independent variable most strongly (or weakly) causes a dependent variable (Baron and Kenny 1986; Frazier et al. 2004; Kraemer et al. 2002; Wu and Zumbo 2008).

In this research, an analysis of variance (ANOVA) was performed to examine the moderation effect of project types on the relationship between the PDS and cost performance raised in Hypothesis 1. The analysis was performed

based on version 23 of the SPSS environment. The basic rationale and the assumptions are described below.

***Selection of Method***

In the construction management discipline, research on moderation effects has been rarely conducted (Xiong et al. 2015; Aibinu and Al-Lawati 2010; Yang et al. 2012). Yang et al. (2012) tested the moderating effect of project type by conducting a two-way ANOVA when examining the relationship between knowledge management and project performance. There are two different methods to examine a moderation effect: regression analysis and ANOVA (Cohen et al. 2003). The methods are selected based on the types of independent variables in question. ANOVA is used when the independent variables are categorical only. The regression analysis method can be applied to both continuous and categorical variables. This research deals with categorical variables (i.e., factors). Both the independent variables (i.e., PDS and project types) have two levels of each factor (i.e., DB and DBB for PDS, residential building and public building for project types). Therefore, this research applied a two-way ANOVA to the moderation analysis model based on a 2 (PDS) × 2 (project types) factorial design.

***Type of Moderator***

There are four types of moderator variables, as shown in Table 3.1: homologizer, quasi-moderator, pure moderator, and other variables not related to moderation (Sharma et al. 1981). If a variable does not have an interaction effect with the independent variables and has a relationship with dependent or independent variables, then the variable turns out not to be a moderator.

**Table 3.1** Type of moderator variable (excerpted from Sharma et al. 1981)

| Interaction | Relationship with dependent/independent var. | No relationship with dependent/independent var. |
|---|---|---|
| No interaction effect with independent var. | Independent var.<br>Exogenous var.<br>Predictor | Homologizer |
| Interaction effect with independent var. | Quasi-moderator | Pure moderator |

Note: var. = variable

This research examined the type of variables using a statistical test described in the next chapter, then determined the type of moderator. Depending on the type of moderator, the function of the variable can be changed from the influential factor in the relationship between independent and dependent variables to one of the simple other variables (e.g., independent, exogenous, predictor).

### *Type of Interaction Analysis and Main Effects*

The type of interaction effect is determined by the appearance of crossed lines in a visualization of the moderation effect. If the visualized moderation effect presents crossed lines, the type of moderation effect is determined to be disordinal. In this case, the main effects of each independent variable do not need to be considered; only the interaction effect between the independent variables will be discussed.

### *Level of Significance*

The significance level was decided according to previous research, as mentioned in the earlier part of this section. A two-tailed test was used. Therefore, the $p$-value (i.e., two-tailed significance value) had to be less than or equal to 0.05.

### *Post Hoc Test*

A post hoc test was used to examine the magnitude of the mean differences between project types (i.e., residential and public buildings). Bonferroni's multiple comparisons were performed for the test. The results compared the mean differences in cost growth between DB and DBB projects, using project type as a moderator variable. The visualization of the moderation effects shows the differences calculated in the post hoc test.

## 3.2 Path Analysis for Mediation Model

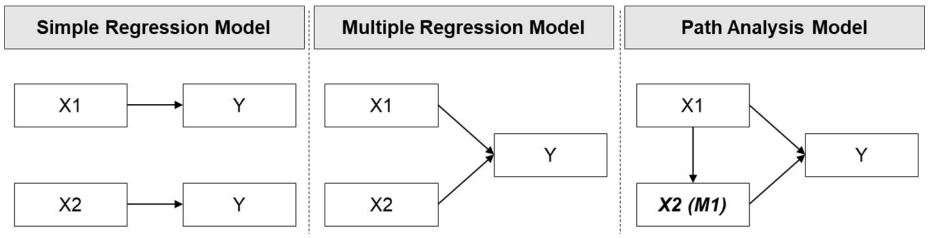
A path analysis method using the R program and Lavaan package (Rosseel 2012) was adopted to examine the mediation effect raised in Hypothesis 2. Mediation effect analysis is a causal model (Rose et al. 2004; Wengener and Fabrigar 2000) that explains the process of "why" and "how" a cause-and-effect happens (Baron and Kenny 1986; Frazier et al. 2004). Hence, a mediational analysis attempts to "identify the intermediary process that leads from the independent variable to the dependent variable" (Muller et al. 2005, p. 852). In other words, in a simple mediational model, the independent variable is presumed to cause the mediator, and in turn, the mediator causes the dependent variable. For this reason, a mediation effect is also termed an indirect effect, surrogate effect, intermediate effect, or intervening effect (MacKinnon et al. 2002; Wu and Zumbo 2008).

### 3.2.1 Introduction to Path Analysis

Path analysis, which is a form of structural equation modeling (SEM), is a technique to analyze the influential relationships not only between independent and dependent variables but also among different independent variables simultaneously (Loehlin 1998; Kline 2011). It performs a causal

analysis using a theoretically grounded model and a covariance (or correlation) matrix. Further, it examines a hypothetical test using empirical data, enabling the identification of both direct and indirect effects.

Path analysis models are distinguished from multiple regression models, as follows: consider the multiple regression model Y = X1 + X2. The regression coefficients are interpreted to determine the increase in Y when X1 is increased by 1 and X2 is kept constant. However, this assumption is counterfactual if X1 has a causal influence on X2. If X1 increases X2 and X2 increases Y in succession, the regression coefficient of X1 underestimates X1's causal influence on Y. Path analysis incorporates the causal influence of X1 on X2 and successfully estimates the causal influence of X1 on Y. Figure 3.2 compares various regression models that consist of simple regression models, multiple regression models, and path analysis models. Each variable describes the relationship between independent, intervening, and dependent variables.




Note: X1, X2 = independent variables; Y = dependent variable; M1 = intervening variable (i.e., mediator)

**Figure 3.2** Comparison of regression models

***Basic Steps of Path Analysis Based on SEM***

The path analysis model was conducted following the basic steps of forming an SEM (Kline 2011, 2018). Figure 3.3 demonstrates the flowchart of these steps, also listed and discussed below.

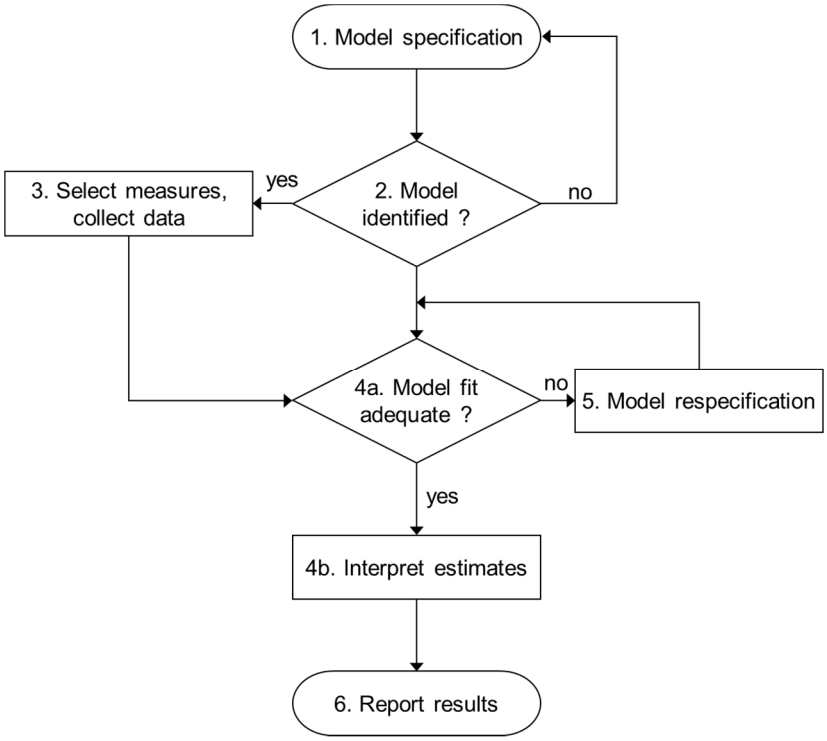



**Figure 3.3** Flowchart of the basic steps of the path analysis (excerpted from Kline 2011)

1. Specify the path model.
2. Evaluate the path model identification (if not identified, go back to step 1).

3. Select the operational measures and collect, prepare, and preprocess the data.
4. Estimate the path model:
    a. Evaluate the path model fit (if it is poor, skip to step 5).
    b. Interprete parameter estimates.
5. Re-specify the path model (return to step 4a).
6. Report the model results.

The model specification allowed for the testing of Hypothesis 2. It depicted conceptual models providing theoretical variables of interest and expected causal relations. It consisted of endogenous and exogenous variables. Every endogenous variable has at least one cause, and the exogenous variables in this research were independent variables which do not display their causes in the path model. The conceptual models had to be translated into statistical models that eventually were examined using the sample data. The statistical model was identified to derive a unique estimate of every model parameter whenever theoretically possible. Evaluating the model fit determined how well the path model explained the collected data. After the model fit, the parameter estimates were interpreted. The final step was to present the results of the analysis.

### 3.2.2 Core Techniques for the Mediation Model

The path analysis model in this research integrated the factors attributed to two stakeholders (the project owner and the contractor). In a multiple regression model, both the PDS and bidding characteristics were independent variables that affected cost growth. In contrast, the path analysis model identified influential relationships and estimated the effects of the PDS and bidding characteristics on cost growth. Path analysis combines theory and data to estimate the causal effects of variables. A theoretical model was built based on the research hypothesis and a literature review, following which real-world data were incorporated in the theoretical model. Finally, the model was used to test the research hypothesis. The model consisted of three main methods: 1) model fit assessment, 2) multi group analysis, and 3) the bootstrap method.

***Model Fit Assessment***

Following the theoretical path model, various path diagrams were postulated based on a range of literature references. The model fit of each diagram was examined prior to interpreting any coefficients from it (Loehlin 1998; Kline 2011). In this research, two alternatives to the path diagram were examined using the scaled $\chi^2$ test (Satorra and Bentler 2001).

### *Multi-Group Analysis*

A multi-group analysis was conducted to verify the moderation effect of project types on the cost growth process. The specific project types of building and civil projects were selected for the path model analysis.

### *Bootstrap Method*

The typical method for validating the statistical significance of an indirect effect is to estimate each path's coefficient and then conduct a Sobel test (Sobel 1982; Xiong and Xia 2014; Moon 2015). However, to perform a more robust analysis, this research used the bootstrap method, rather than a normal theory test, to estimate both the direct and indirect effects, as well as the standard errors (S.E.) in the path model (MacKinnon et al. 2004; Cheung and Lau 2008; Hayes 2009).

The estimated coefficients and the confidence intervals at .95 were obtained through bootstrapping. The value of S.E. and *p*-value based on a normal theory were calculated as a reference. The value of .95 confidence intervals should not include zero value to be statistically significant.

## 3.3 *t*-Test for Cost Performance Comparison of PDS

An independent samples *t*-test with two tails was performed to examine whether the mean value difference in cost growth for DB and DBB building and civil projects was statistically significant. Most research related to evaluating the performance of PDSs have used a *t*-test to examine the mean value differences of different performance metrics (Pocock et al. 1996; Shrestha et al. 2007; Perkins 2009; Minchin et al. 2013; Tran et al. 2018). The *t*-test was performed based on version 23 of the SPSS environment. The underlying assumptions and rationale for the test are described below.

***Independent Sampling***

There are two types of *t*-tests based on the types of sampling: dependent samples and independent samples. An independent samples *t*-test was chosen for this research based on the experimental conditions. Two different PDS samples (DB and DBB delivery systems) were used for the independent variable. An independent samples *t*-test is also called an independent-means or independent-measures *t*-test. It is used when there are two experimental conditions, and different participants are assigned to each condition (Field 2009).

### *Normal Distribution*

*t*-tests are parametric tests based on normal distribution. Therefore, the test assumes that the sampling distribution is normally distributed (Field 2009). If a degree of freedom (df) is more than 30 and near 100, the data are assumed to be normally distributed.

### *Level of Significance*

The significance level was decided according to previous research, as mentioned earlier in this section. A two-tailed test was used. Therefore, for the null hypothesis of the test to be rejected, the *p*-value (i.e., two-tailed significance value) must be less than or equal to 0.05.

### *Equality of Variances*

Levene's test was used to test the equality of variances (Field 2009; Minchin et al. 2013). It examined the null hypothesis that the variances in the cost performance of both the DB and DBB systems were equal (homogeneity of variance), as shown in Equation 3.1.

$$H_0: \sigma_{DB} = \sigma_{DBB} \qquad \text{(Eq. 3.1)}$$

If Levene's test was significant at $p \leq 0.05$, then it would be concluded that the null hypothesis was violated. In that case, the variances would be significantly different (i.e., the assumption of homogeneity of variances would be rejected). However, if the test was not significant (i.e., p-value > 0.05), then the variances would be determined to be roughly equal (Field 2009).

***The Null Hypothesis of the t-Test***

A *t*-test can be used to test whether two group means are statistically different or not (Field 2009). In this research, the null hypothesis was when the mean values of cost growth for DB and DBB samples were statistically equal, as shown in Equation 3.2.

$$H_0\colon\ \mu_{DB} = \mu_{DBB} \qquad \text{(Eq. 3.2)}$$

If the *t*-test was significant at $p \leq 0.05$, then it would be concluded that the null hypothesis was violated. Therefore, the mean values of cost growth for DB and DBB samples would be found to be significantly different.

## 3.4 Ensemble Learning for Moderation Effect Verification

The ensemble learning model was developed to verify the moderation effect of project types. Project cost overruns during the construction phase are caused by various reasons. Those reasons are generated in each phase of a project life cycle (e.g., project planning, procurement, construction, maintenance). The earlier the project phase, the higher the risk and uncertainties. Therefore, the major contributing factors to the magnitude of cost overruns are derived from the earlier project phases. In the procurement phase (i.e., bidding stage), information combined with project characteristics is generated; bidding characteristics (e.g., award method, number of bidders, winning bid amount, bid to estimate rate, number of joint ventures) in combination with project characteristics (e.g., project type, delivery method, project duration) are the main contributors to cost overruns during the construction phase. Project types can be examined as a key predictor of cost overruns using the ensemble prediction model.

### 3.4.1 Selection of Ensemble Learning Approach

Numerous methods have been applied to predict project cost overruns. They include the applications of AI techniques and statistical methods.

Research in this area has been hampered by the lack of available cost data from the construction industry and state-of-the-art techniques for the prediction model. Some studies have investigated the development of prediction models that use artificial and fuzzy neural networks (Georgy et al. 2005), multilayer feed-forward and general regression neural networks (Petroutsatou et al. 2012), regression analysis that compares traditional and weighted least squares techniques (Sousa et al. 2014), and Frequentist and Bayesian approaches (Behmardi et al. 2015). Principal components analysis and support-vector regression have been used to predict project costs (Son et al. 2012). The Son et al. (2012) study used 64 variables as input data and produced a better predictive performance with the hybrid PCA-SVR model. However, the key contributors to cost overruns cannot be distinguished due to the combination of input data that reduces attributes (i.e., extracting features). Additionally, previous studies tend to only focus on increasing prediction accuracy rather than identifying individual key factors that most affect cost overruns.

Recent studies have employed advanced data-mining techniques to achieve better prediction performance. The ensemble learning technique is getting popular in various areas because the model performance with multiple learnings outperforms the single learning model significantly (Maghrebi et al. 2016; Yang et al. 2016). The ensemble-learning approach combines several methods to obtain better predictive performance than the individual methods

achieve by themselves. This approach is well-known for improving prediction performance (Rokach 2010). In the construction management area, the ensemble learning approach has been recently applied and its use is limited compared with single learning algorithms (Cao et al. 2018).

Wang et al. (2012) used artificial neural networks ensemble for predicting classification models to investigate the relationship between the status of early planning and project performance. Two ensemble classifier prediction models provided average accuracies of 76% and 84%, respectively. However, the collected data were limited to a questionnaire survey rather than empirical data. Williams and Gong (2014) employed a text-mining method where texts from projects of the California Department of Transportation in the US were processed and then transformed using support-vector decomposition into a numeric value that was combined with other data and submitted to a stacking ensemble classifier. The addition of text data was found to improve the prediction results. The ensemble stacking model produced the best prediction accuracy compared to other single models, even though it presented an average accuracy of 43.72%. However, they used only bidding characteristics as input data, therefore it is assumed that incorporating other bidding and project characteristics as input could enhance the model's cost predictions. Ahiaga-Dagbui and Smith (2014) compared the cost overrun model performances between single algorithms and the ensemble learning model. The study

addressed the problem of insufficient information for reliable predictions, concluding that the accuracy of initial cost estimates could be improved with the ensemble learning technique. Cao et al. (2018) predicted bidding prices using an ensemble learning model that was comprised of other algorithms could provide better accuracy. They found that an ensemble learning model can predict resurfacing project unit price bids with more accuracy than multiple linear regressions and Monte Carlo simulation models.

Previous efforts show that AI techniques and statistical methods have been successfully employed for project cost predictions (Georgy et al. 2005; Gkritza and Labi 2008; Petroutsatou et al. 2012; Sousa et al. 2014; Behmardi et al. 2015). Additionally, cost prediction model techniques have been improved by combining multiple algorithms such as ensemble learning methods rather than applying a single algorithm as presented in the previous paragraphs (Wang et al. 2012; Williams and Gong 2014; Ahiaga-Dagbui and Smith 2014; Cao et al. 2018). These prediction trends show that interest has increased in applying various modeling techniques, both hybrid and ensemble, to construction costs.

The main reason to apply an ensemble-based model to predict cost overruns is to reduce the overall risk of making a poor selection. In some cases, combining the outputs of multiple classifiers (e.g., expert) by averaging may reduce the risk basing a decision on a poorly performing classifier (Polikar

2006). To further explore prediction performance, this research used an ensemble learning method to develop a project cost overrun classification model.

Stacking among various ensemble learnings is a technique for achieving the highest generalization accuracy by using a meta-learner (Rokach 2010; Wolpert 1992). Stacking ensemble learning can provide improved prediction results by using several different algorithms (i.e., classifiers) and then combining their results to get the best prediction. This model uses the stacking technique where an ensemble of classifiers is first created whose outputs are used as inputs to a second-level meta classifier to learn the mapping between the ensemble outputs and actual correct classifiers (Polikar 2006). It was developed using the RapidMiner environment (Mierswa et al. 2006). RapidMiner is an open-source software system that allows for the rapid development of data-mining models.

### 3.4.2 Classification Learning Algorithms

In this model, different classification algorithms were used to classify project data as the first level of basic classifiers, and the if-then rule as a meta-leaner was adopted to select which of the two model predictions would be used.

The three classification algorithms employed are the 1) Ripple-down and 2) K-star classification algorithms. The if-then rule employed is the 3) Rule Induction algorithm. These algorithms have been validated to have reliable accuracy in a previous study using construction data (Williams and Gong 2014).

***Ripple-Down***

The Ripple-Down is a machine learning technique that automatically generates a set of classification rules from the input data (Gaines and Compton 1995; Witten et al. 2011). It learns rules with exceptions by generating a default rule. The default or top-level rule is the class of output that most frequently occurs. The algorithm then uses incremental reduced-error pruning to determine exceptions with the smallest error rate and determines the best exceptions for each exception and iteration. In the construction cost overrun prediction area, it has been used to create a classification rule using bidding stage data (Williams 2007; Williams and Gong 2014).

***K-Star***

K-Nearest Neighbors (KNN) methods are widely used in the project cost prediction area (Maghrebi et al. 2016). K-star uses the same form of KNN (Witten et al. 2011). It is a type of algorithm called a lazy learner, an instance-based learning scheme developed by Cleary and Trigg (1995). Witten et al.

(2011) described the K-star algorithm as a lazy classifier where the training instances are stored and are not employed until classification time. This algorithm uses a generalized distance function, while KNN uses the Euclidean distance function.

***Rule Induction***

The Rule Induction operator of the RapidMiner environment was used to generate rules for selecting the output of the two classification algorithms (Witten et al. 2011). The algorithm used to generate the rule is a propositional rule learner called "Repeated Incremental Pruning to Produce Error Reduction" (Cohen 1995). Starting with the less prevalent classes, the algorithm iteratively increases and prunes the rules until no positive examples are left or the error rate is greater than 50%. In the growth phase, for each rule, greedy conditions are added to the rule until it becomes perfect (i.e., 100% accurate). The procedure tests every possible value for each variable and selects the condition with the highest information gain. In the pruning phase for each rule, any final sequences of the antecedents are pruned using the pruning metric $p/(p + n)$ (Rapidminer studio 2017). Figure 3.4 shows how the if–then rule was introduced using RapidMiner to combine the outputs of the classifiers and select the level of cost overruns.

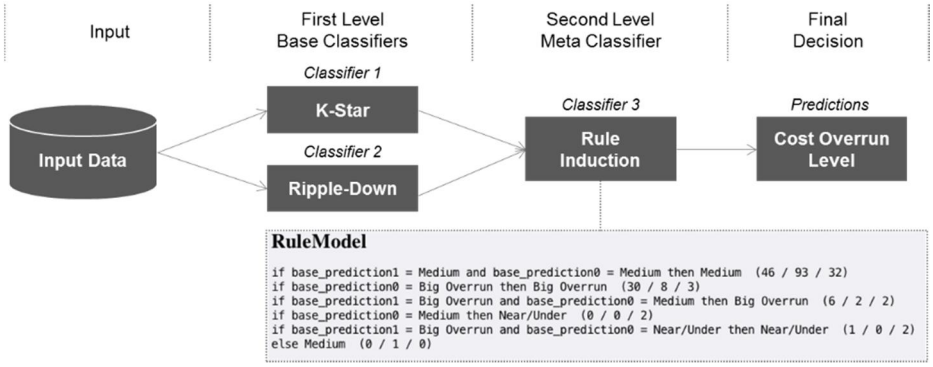



**Figure 3.4** Rule to select the overrun level based on the classifier outputs

### 3.4.3 The Level of Cost Overrun for the Classification Model

Depending on the project phase, the numerical value (i.e., continuous variable) is sometimes useful. For example, in the planning phase, the exact value is needed to prepare a bid or estimate a project cost. However, some other times, knowing the magnitude of the risk (i.e., level, range) rather than a numerical value is more useful for detecting risk before the contract is finalized in the bidding stage. It is more useful to provide the risk level of a cost overrun (e.g., near/under, medium, high risk) rather than produce a cost overrun numerical value for practitioners to help them recognize screen project(s).

A number of studies have used a cost growth range (i.e., cost overrun level, group, magnitude) when they compare or assess cost overruns (Jahren and

Ashe 1990; Ganuza-Fernández 1996; Williams 2002; Pérez-Castrillo and Riedinger 2003; Lakshminarayanan and Sackrowitz 2005; Williams et al. 2005). The size of the cost growth ranges used in previous studies varies from 1% to 20%. Lakshminarayanan and Sackrowitz (2005) and Williams et al. (2005) used the ranges of 5%, 10%, and 20%. Jahren and Ashe (1990) concluded that contracts with an award amount less than the government estimate were more likely to have cost overrun rates above 5%. This value was applied to this model as a threshold level.

The upper threshold level of cost overruns was determined through previous studies subjected to project claims between stakeholders. More than a 20% cost overrun is a claims issue, and if the cost overrun claim stays under 20% of the contracted price, firms are subject to very limited control. However, projects with cost overruns of more than 20% are subject to a strict control system (Ganuza-Fernández 1996; Pérez-Castrillo and Riedinger 2003). This value was also applied to this model as a threshold level. Therefore, 5% and 20% cost overruns were used as the threshold levels. To further confirm these threshold levels were appropriate, interviews were conducted with five officials from the city of Seoul project management team who have more than ten years of experience in this field. In fact, they carried out most of the projects included in the database.

In this research, the ensemble learning model produced a prediction of the level of cost overruns that would occur during construction execution. Projects were classified as near/under run, medium, or high. When the value of the cost overrun was negative, it was called a cost underrun. Near/under run were projects completed with a cost increase of less than 5%. Medium projects were projects completed with a cost increase between 5% and 20%. High overrun projects were completed with cost increases of more than 20%.

### 3.4.4 Ensemble Learning Model Validation and Evaluation

To validate the ensemble model, the prediction performance between conventional (i.e., single-learning) models and the stacking ensemble model were compared using the same environment. The prediction performance for the classification models was evaluated by 10-fold cross-validation based on three performance metrics: prediction accuracy, precision, and recall (Chou and Lin 2013; Williams and Gong 2014). Prediction accuracy is the most important metric when comparing algorithms because it represents the ability of each algorithm to identify the correct class (Maghrebi et al. 2016). Precision and recall (i.e., sensitivity) are extended versions of prediction accuracy (Chou and Lin 2013).

A cross-validation scheme was employed to prevent overtraining of the data and to minimize bias associated with the sampling of training and testing data (Witten et al. 2011; Chou and Lin 2013). The cross-validation operator was a nested operator. It had two sub-processes: training and testing. The training sub-process was used to train the cost prediction model, and the trained model was then applied to the testing sub-process to make predictions. The performance of the model was also measured during the testing phase. The data from the projects was partitioned into $k$ subsets of equal size. Of the $k$ subsets, a single subset was used as the testing dataset, and the remaining $k - 1$ subsets were used as the training data set. The cross-validation process was then repeated $k$ times with each of the $k$ subsets used exactly once as the testing data. The $k$ results from the $k$ iterations were then averaged (or otherwise combined) to produce a single estimation (Rapidminer studio 2017).

This model used a $k$ value of '10' which most previous studies used (Liu et al. 2018; Maghrebi et al. 2016; Witten et al. 2011) since Kohavi (1995) confirmed that 10-fold were optimal for computation time and variance. Therefore, the dataset was divided by 10, of which 9/10ths were used for the training model and the remaining tenth of the dataset used for testing the model.

### 3.4.5 Data Preprocessing

***Identification and Removal of Outliers***

The RapidMiner environment provided the capability to automatically detect and filter outliers. It implemented the algorithms developed by Ramaswamy et al. (2000) that ranked each project according to its distance to its *k*th nearest neighbor and then declared that the top *n* points as the outliers. Removing the five greatest outliers improved the performance of the prediction model.

***Normalization of the Original Estimated Data***

The original estimated magnitude values widely varied. Normalizing the original bid amount improved the accuracy of the predictions. The purpose of statistical normalization was to convert the data into a normal distribution with mean = 0 and variance = 1. The formula for statistical normalization is

$$Z = (X - u)/s. \qquad \text{(Eq. 3.3)},$$

where vector "*X*" denotes the attribute values, *u* is the mean of the attribute values, and *s* is the standard deviation. First, *u* was subtracted from *X* and this difference was divided by *s*. Using this formula, another vector *Z* was obtained

that has a normal distribution with zero mean and unit variance. This vector is also called the standard normal distribution $N(0, 1)$.

***Discretization of the Numeric Data***

The discretization was performed by simple binning. The range of numerical values was partitioned into segments of equal size where each segment represented a bin. Numerical values were assigned to the bin to represent the segment that covered the numerical value. Four bins were used for each numerical variable.

## 3.5 Summary

In this chapter, various methods to validate and verify the research model were introduced: statistical methods and data mining approaches were applied to moderation and mediation analysis, and statistical test of mean difference in cost performance between DB and DBB systems for project types.

First, to ascertain whether project types moderate the effect of PDS on cost performance raised in Hypothesis 1, this research conducted two-way ANOVA. The basic rationale and the assumptions were introduced: selection of method,

types of moderator, the type of interaction analysis and main effects, level of significance, post hoc test. For the verification of the moderation effect, multi-group analysis in Section 3.2.1 and ensemble learning stacking methods in Section 3.4 were introduced.

Second, a path analysis method using the R program and Lavaan package was adopted to test the mediation effect of Hypothesis 2. The analysis was conducted to explain how PDS effects on cost performance through bidding characteristics indirectly. The basic rationale and the assumptions were introduced: theoretical background of path analysis, core techniques for the mediation analysis (i.e., model fit assessment, multi-group analysis, and bootstrap method).

Finally, an independent samples *t*-test with two tails to compare the cost performance of DB and DBB was introduced. The test was performed to examine whether the mean value difference of cost growth for DB and DBB building and civil projects were statistically significant. The basic rationale and the assumptions were introduced: independent sampling, normal distribution, level of significance, equality of variances, and the null hypothesis of the *t*-test.

# Chapter 4

# Moderation Model

This chapter describes how the study developed, validated, and verified the moderation effect analysis model that analyzed under what circumstances project type moderates the effect of PDS on cost performance (Hypothesis 1). In the moderation model development process, a conceptual and a statistical moderation model was established. Data collection and analysis, exploring variable attributes through data analysis, and descriptive statistics of variables were performed. For the validation and verification of the moderation model, the interaction analysis of project type, and visualizing the moderation effect, multi-group analysis, and ensemble-stacking learning were performed.

## 4.1 Model Development

### 4.1.1 Conceptual Moderation Model

To show how Hypothesis 1 was tested, the moderation model was split into conceptual and statistical diagrams (Hayes 2013). Conceptually, the moderation model is depicted in Figure 4.1. The diagram represents a process

in which the effect of PDS on cost performance is influenced or dependent on project type, as reflected by the arrow pointing from project type to the line from PDS to cost performance.

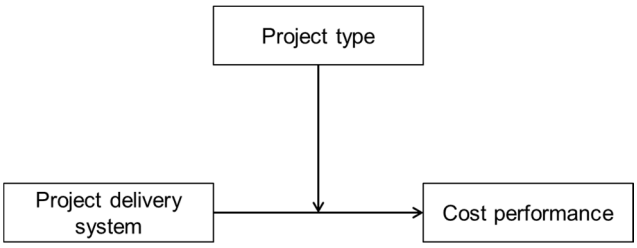



**Figure 4.1** Moderation model depicted as a conceptual diagram

Table 4.1 depicts the conceptual definitions of the variables in the moderation model.

**Table 4.1** Conceptual definitions of variables for moderation model

| Name | Conceptual definition | Type of variable | Type of scale | |
|---|---|---|---|---|
| Project delivery system | Type of delivery system: DB and DBB | Independent | Nominal | Qualitative |
| Project type | Type of facility | *Moderating* | Nominal | Quantitative |
| Cost growth | Percentage growth from contract amount (%) | Dependent | Ratio | Quantitative |

Note: DB = design-build; DBB = design-bid-build.

The conceptual diagram is different in form from its corresponding statistical diagram, which represents how such a model is represented in the form of an equation.

### 4.1.2 Statistical Moderation Model

The statistical diagram corresponding to the conceptual model requires not two but three antecedent variables, and project type is one of those antecedents as described in Figure 3.2.

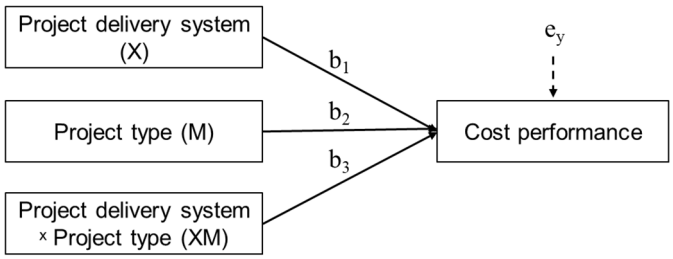



**Figure 3.2** Moderation model as a statistical diagram

Statistically, the moderation effect analysis was conducted by testing for an interaction between project type (M) and PDS (X) in a model of cost performance (Y). With evidence that X's effect on Y was moderated by M, we then quantified and described the contingent nature of the association or effect

by estimating X's effect on Y with various values of the moderator, an exercise known as probing the interaction. Equation 3.1 shows the standard multiple linear regression model. "$b_3$" represents the interactive role between PDS and project type.

$$Y = b_{01} + b_1\mathrm{X} + b_2\mathrm{M} + b_3\mathrm{XM} + e_{\mathrm{y}} \qquad \text{(Eq. 3.1)}$$

The moderation effect is interpreted depending on both the statistical significance and the sign of $b_3$ (Cohen et al. 2002). If the model result of $b_3$ is statistically significant, project types are confirmed to moderate the effect of PDS on cost performance.

## 4.2 Data Collection and Analysis

### 4.2.1 Data Collection

The database used for conducting this research was collected with the research hypotheses in mind. All the project data for this research were obtained from two departments of the Seoul Metropolitan Government: the Department of Civil Infrastructure and Department of Architectural Building. The data are limited to Seoul city, which is the capital and largest metropolis with half of all the residents of South Korea, officially known as the Seoul Special City[2].

The database includes 234 public-sector projects completed in Seoul between 1998 and 2013; each project cost more than US$ 5 million. The contract amount on average for DB projects exceeded US$ 100 million, whereas that for DBB projects was between US$ 30-70 million. The minimum price was US$ 5.3 million and the maximum was approximately US$ 540 million. The number of projects using DB versus DBB were relatively evenly

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[2] http://english.seoul.go.kr/?tr_code=rsite

distributed where DB was 97 (41.5%) samples and DBB accounted for 137 (58.5%) samples. According to reports by the Seoul Metropolitan Government authorities, four projects were considered outliers and excluded from the dataset since they reported excessive cost growth resulting from government policies and social conditions. Not only the moderation model but also other models are flexible to choose their own dataset out of the original database according to project types. Each model should be consistent with the data utilized related to its assumptions (Bollen 1989).

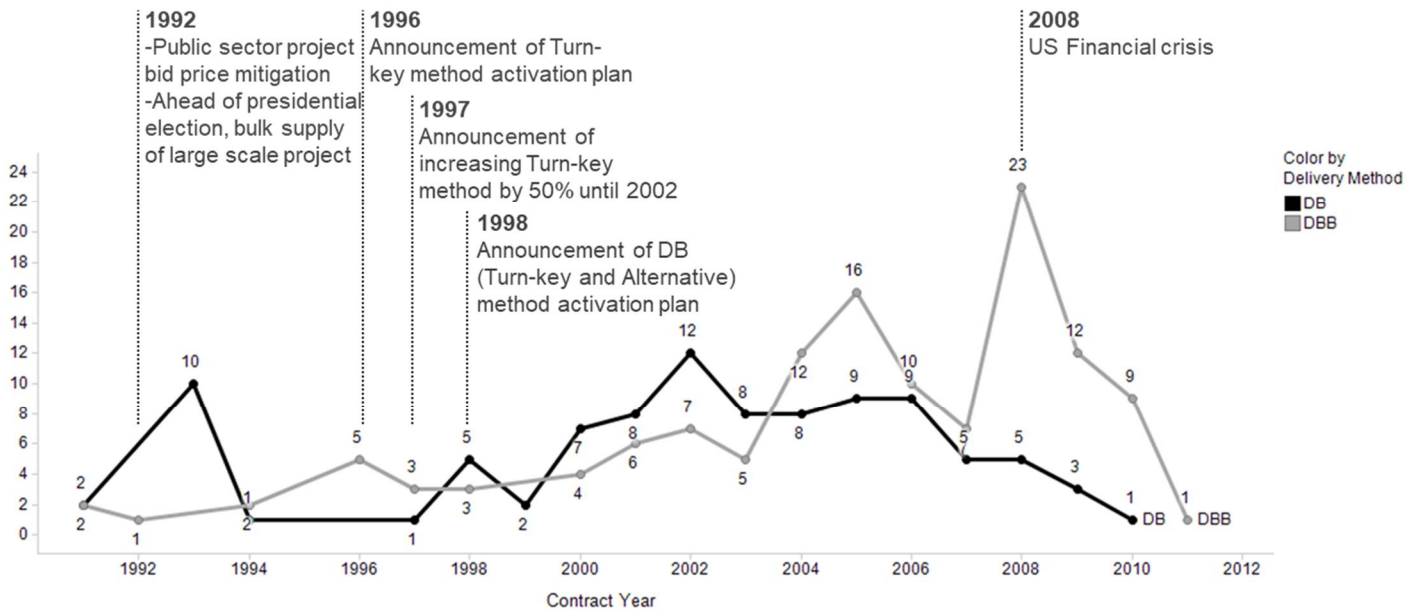
### 4.2.2 Data Analysis

The selected variables for the moderation model were PDS, cost growth, and project type. An analysis of the variables was conducted using the collected database as described below.

***Project Delivery System***

A PDS-market-share analysis by contract year from 1992–2011 in Seoul is shown in Figure 3.3. In addition, announcements of governmental policies on PDS were researched and matched up with the market share. Figure 4.3 shows that the number of DB projects had increased due to a governmental policy implemented beginning in 1992 and that both the DB and DBB system

market shares showed similar trends in terms of the number of contracts. The contracts of both the DB and DBB had decreased since 2008 because of the US financial crisis. This analysis indicates that construction projects were influenced by government policy and economic situations. Therefore, price fluctuations that reflect the economic situation were excluded from the dataset because it was assumed that they would distort the evaluation of the PDS on cost performance (Carr 2005).




Note: DB = design-build; DBB = design-bid-build; PDS = project delivery system

**Figure 4.3** Public sector PDS market-share analysis in Seoul, South Korea (excerpted from Moon 2015)

### *Cost Growth*

To confirm cost growth as a useful cost performance metric, the collected data were analyzed. Using the database, a line graph of cost growth rates was produced according to the actual dates of project completion. The cost growth rates from the dataset consisted of price fluctuation rates and change order rates. Figure 3.4 shows that both cost growth and change order rates had similar trends; however, the projected price fluctuation rates was large in both lines. Cost performance in the current dataset was dominated by change orders rather than price fluctuations. Therefore, the operational definition of cost growth was measured in percentage terms by comparing the final construction cost, which was the price fluctuation cost, to the initial contract cost.

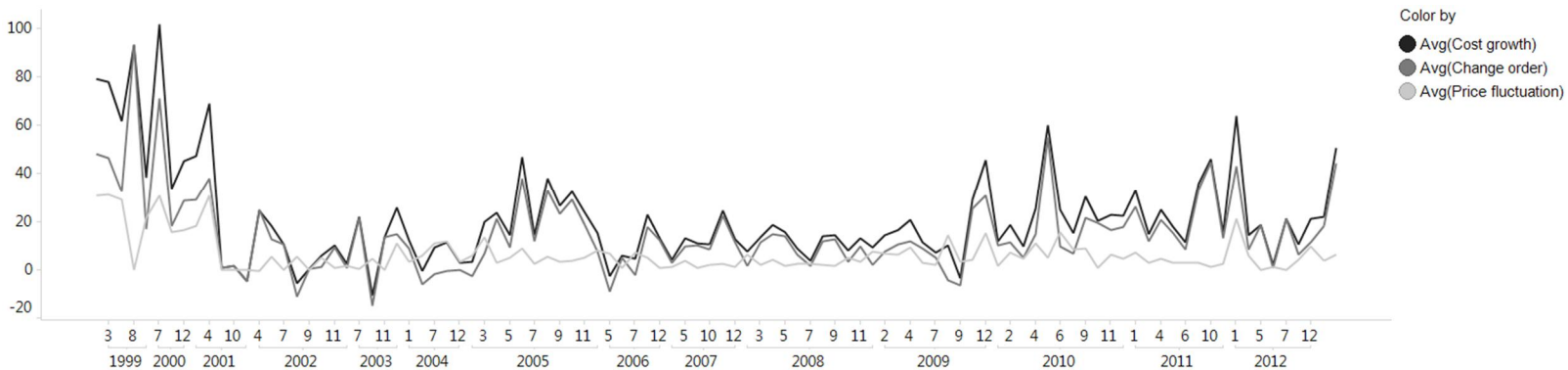



**Figure 4.4** Components of cost growth as a performance metric

***Project Type***

The project types within the collected data included civil infrastructure projects, public building projects, landscaping, and mechanical facilities as shown in Table 4.2. The data available for the projects included two kinds of project types. Project type as the dataset variable was called a general project type, and a sub-project type was a sub-category of the general project type. Building projects included residential buildings, public buildings, community centers, offices, libraries, public schools, and so on. Civil projects include roads, sewerages, subways, water supplies, and river bridges.

**Table 4.2** Project type and sub-project type

| Project type | Sub-project type |
|---|---|
| Civil | Sewerage |
| | Subway |
| | Road |
| | River |
| | Water supply |
| Building | Public building |
| | Residential building |
| Mechanical Facility | Mechanical facility |
| Landscaping | Landscaping |

Table 4.3 presents mean values (i.e., average percentage) of cost growth associated with different PDSs and project types. For general civil, building, and facility project types, the DB delivery system had, on average, a lower level of cost growth than DBB projects. Landscaping projects were only executed using DBB.

**Table 4.3** Average percentage of cost growth according to PDS and project type

| Project type | Mean value (S.D.) | | Mean difference | Sample size of DB/DBB |
|---|---|---|---|---|
| | DB | DBB | | |
| Civil | 13.43(23.39) | 20.11(33.22) | 6.68 | 49/61 |
| Building | 9.72(13.50) | 14.49(11.28) | 4.77 | 35/56 |
| Mechanical facility | 1.54(4.21) | 20.73(22.97) | 19.19 | 13/4 |
| Landscape | - | 36.67(24.41) | NA | 0/16 |
| Total | 10.50(18.86) | 19.76(25.71) | 9.26 | 97/137 |

Note: DB = design-build; DBB = design-bid-build; S.D. = standard deviation; NA = not applicable

The list of Table 4.4 shows that the superiority of the DB system was not obvious for some specific sub-project types of construction. For road and water-supply projects, the average cost increase using DB was less than that of those using DBB. The table also shows that the subway projects in this data were only constructed as DB projects, whereas sewerage and landscape projects were only constructed as DBB projects.

**Table 4.4** Average percentage of cost growth according to PDS and sub-project type

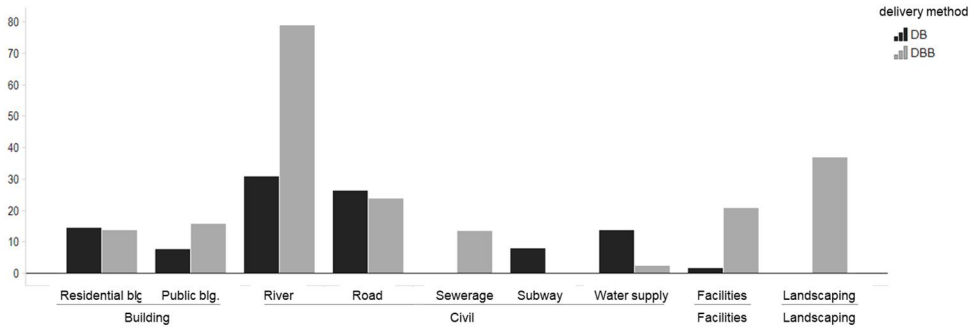
| Sub-project type | Mean value (S.D.) | | Mean difference | Sample size of DB/DBB |
|---|---|---|---|---|
| | DB | DBB | | |
| Sewerage | - | 13.30(15.18) | NA | 0/8 |
| Subway | 7.78(20.65) | - | NA | 32/0 |
| Road | 26.26(30.09) | 23.62(32.89) | -2.64 | 10/36 |
| River | 30.68(19.67) | 78.84(70.29) | 48.16 | 3/3 |
| Water Supply | 13.61(13.81) | 2.38(9.95) | -11.22 | 4/14 |
| Public building | 7.63(14.24) | 15.53(13.81) | 7.90 | 24/26 |
| Residential building | 14.29(10.91) | 13.58(8.67) | -0.71 | 11/30 |
| Mechanical facilities | 1.54(4.21) | 20.73(22.97) | 19.19 | 13/4 |
| Landscape | - | 36.67(24.41) | NA | 0/16 |
| Total | 14.54(16.23) | 25.58(24.77) | 11.04 | 97/137 |

Note: DB = design-build; DBB = design-bid-build; S.D. = standard deviation; NA = not applicable

To examine why the superiority of the DB system was not obvious for some project types, project types was considered to be a confounding factor. Figure 4.5(b) shows the visualization of Table 4.4 as a bar chart, which simplifies the comparison between the DB/DBB projects in total (Figure 4.5(a)) and DB/DBB projects broken down by project types (Figure 4.5(b)).


Note: DB = design-build; DBB = design-bid-build

**Figure 4.5(a)** Average percentage of cost growth for PDS only




Note: DB = design-build; DBB = design-bid-build

**Figure 4.5(b)** Average percentage of cost growth for PDS with specific project types (bar chart visualization of the data listed in Table 4.4)

Without considering the break down by project types, the DB delivery system always presents lower cost growth than that of the DBB system, meaning the DB system outperforms the DBB system. However, the cost growth of PDSs varies depending on project types. This result confirms that project type plays a role as an influential factor on the relationship between PDS and cost performance, and should be identified as third factor in the comparison of DB and DBB delivery systems.

***Descriptive Statistics of Input Variables***

The developed moderation model was applied to the construction project of 90 samples. Samples were categorized into two project types (residential buildings and public buildings) where the sample sizes were evenly distributed; the residential building project data were comprised of 41 observations (45.6%) and the public building projects data accounted for 49 observations (54.4%). Table 4.5 presents the descriptive statistics of cost growth rates by PDS and project type.

**Table 4.5** Descriptive statistics of cost growth rates associated with project type and PDS

| Project type | PDS | Frequency (%) | Mean value (SD) | Mean difference (%) |
|---|---|---|---|---|
| Residential building | DB | 11 | 12.75 (7.52) | 0.83 |
| | DBB | 30 | 13.58 (8.67) | |
| | Sub-total | 41 (45.6%) | | |
| Public building | DB | 23 | 5.12 (6.97) | 10.41 |
| | DBB | 26 | 15.53 (13.81) | |
| | Sub-total | 49 (54.4%) | | |
| | Total | 90 (100%) | | |

Note: DB = design-build; DBB = design-bid-build; PDS = project delivery system; SD = standard deviation

## 4.3 Model Validation and Verification

### 4.3.1 Moderation Model Results

To examine the effect of a moderator, a two-way ANOVA was conducted. The results are shown in Table 4.6. According to the results, the interaction effect (XM) of PDS and project type was statistically significant ($F = 4.462$, $p$-value $= 0.038 \leq 0.05$).

**Table 4.6** Results of interaction effect by two-way ANOVA (significance test)

| Variable | Sum of Squares | *df* | Mean Square | *F* | *p*-value |
|---|---|---|---|---|---|
| PDS (X) | 613.140 | 1 | 613.140 | 6.144 | .015 |
| Project type (M) | 156.214 | 1 | 156.214 | 1.565 | .214 |
| PDS×Project type (XM) | 445.284 | 1 | 445.284 | 4.462 | .038 |
| Error | 8582.350 | 86 | 99.795 | | |

Note: PDS = project delivery system; *df* = degree of freedom

Hypothesis 1 was tested through interaction analysis. According to the test results, project type had a significant effect on the relationship between PDS and cost performance, playing a moderator role between PDS and cost

performance. In other words, the effect (strength or sign of direction) of PDS on cost performance differs depending on project types. As mentioned in the Research Methodology chapter, the project type variable is determined to be a pure moderator because the main effect of project types on cost performance (dependent variable) was not statistically significant, and the variable had an interaction effect on PDS (independent variable) (Sharma et al. 1981).

Table 4.7 presents the results of the post hoc test using the Bonferroni multiple comparison. The mean difference in cost growth between DB and DBB systems was much bigger in public buildings (mean difference = 10.413 percentage point (pp)[3]) than in residential building projects (mean difference = 0.831 pp).

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[3] pp = percentage points (or percent point) are a way of expressing a change from an original amount to a new amount without using a percent sign. For example, if a company's market share increased from 40 to 44 percent of a total market, this is expressed as an increase of 4 percentage points, or 4 pp (Brechner and Bergeman 2014).

**Table 4.7** Results of post hoc test

| Dependent variable | Project type | PDS | Sample size | Mean | S.E. |
|---|---|---|---|---|---|
| Cost growth | Public building | DB | 23 | 5.119 | 2.083 |
| | | DBB | 26 | 15.532 | 1.959 |
| | Residential building | DB | 11 | 12.747 | 3.012 |
| | | DBB | 30 | 13.578 | 1.824 |

Note: PDS = project delivery system; DB = design-build; DBB = design-bid-build; S.E. = standard error

In the moderation model, the detailed attribution of variables could be considered for future research. The type of scale for both the PDS and project type as nominal variables could be applied to other methods not only two-way ANOVA. For example, logistic regression to model the distribution of nominal variables or an ensemble method that is considered to handle imbalanced classes more robustly could be considered.

### 4.3.2 Visualization of Moderation Effect

Figure 4.6 demonstrates the moderation effect (i.e., interaction effect) of PDS and project type on cost performance because the slopes of residential building and public building projects intersect each other. Therefore, the main

effect of PDS appears wherever it is, and wherever it is reversed. That is, the main effect of the independent variable (i.e., PDS) does not consistently appear, and other results appear depending on mutual combinations with other variables (i.e., project type), meaning that the effect of PDS on cost performance differs depending on project type. The type of interaction effect is disordinal interaction because the lines cross each other. Therefore, the results do not need to consider the main effects of independent variables, only their interaction.

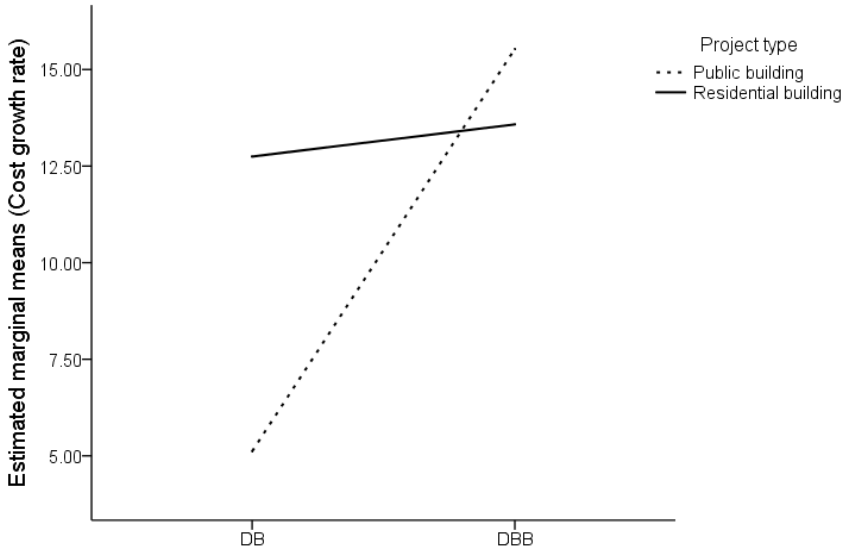



**Figure 4.6** Visual representation of the moderation of the effect of different PDS (X) on cost growth (Y) by project type (M)

### 4.3.3 Model Verification by Multi-Group Analysis

To verify the moderation model results, the dataset from the mediation analysis model was utilized to perform a multi-group analysis. In the multi-group analysis, the first question to be addressed was whether the coefficients were the same across groups (i.e., project types). Accordingly, the groups with the same coefficients and different coefficients for each group were compared. Further, as part of the analysis, a scaled $\chi^2$ test (Satorra and Bentler 2001) was conducted under the assumption of having the same coefficients across groups.

***Input Data Descriptions***

The dataset for the verification was the same as the one used in the mediation model case study. Architectural building and civil infrastructure projects were used as the project type categories.

***Test Results***

If the $\chi^2$ tests for coefficients and error variance between groups showed significance across the groups with a *p*-value of less than 0.05, the results would reveal that the coefficients and error variance of groups were varied between the groups. Table 4.8 shows that the coefficients between groups showed significance (scaled $\chi^2$ difference = 12.345, $df = 5$, $p$-value = 0.030).

Subsequently, it was tested whether the residual variance could be assumed to be the same across groups (allowing the coefficients to be the same for different groups); however, this assumption was not supported (scaled $\chi^2$ difference = 8.371, *df* = 3, *p*-value = 0.039). These results further indicated that the cost performance of PDS depends on project types and supports additional research to further distinguish between project types' effects on PDSs and cost performance.

**Table 4.8** Chi-square test result of multi-group analysis for project type

| Model Fitness | The same coefficients between groups | The same error variance between groups |
|---|---|---|
| $\chi^2$ difference | 12.345 | 8.371 |
| *df* | 5 | 3 |
| *p*-value | 0.030 | 0.039 |
| significant | Yes | Yes |

Note: *df* = degree of freedom; $\chi^2$ = Chi-square

## 4.4 Model Verification by Ensemble Learning Approach

The ensemble learning model was developed to verify the moderation effect of project type by comparing model accuracy, precision, and recall with and without project type as a key predictor of cost overruns (i.e., cost growth). Figure 4.7 shows the structure of the developed stacking ensemble model.

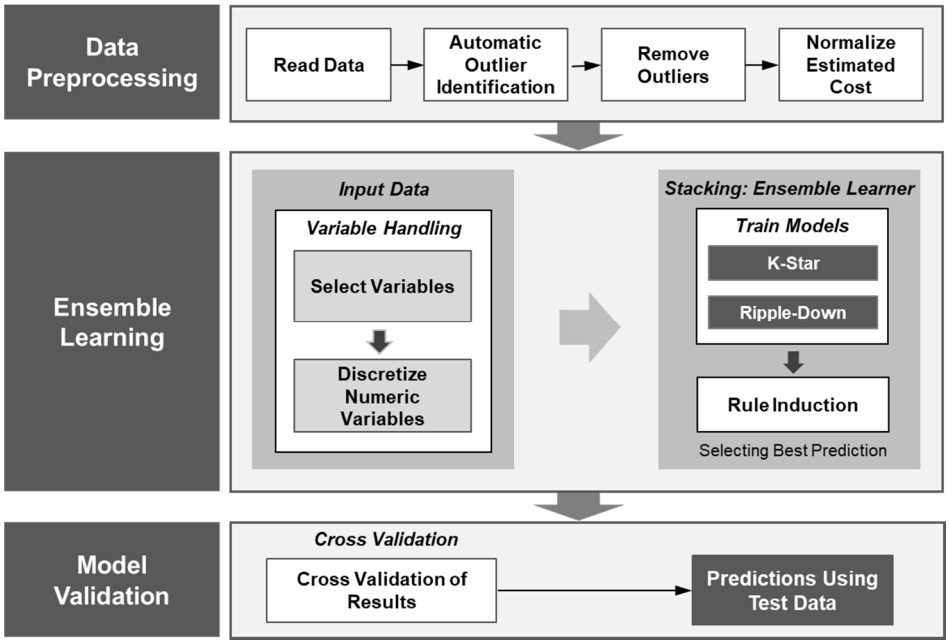



**Figure 4.7** Structure of the ensemble-learning model

The model produced a prediction of the level of cost overruns that would occur during construction execution. Projects were classified as near/under run, medium, and high. Near/under run were projects completed with a cost increase

of less than 5%. Medium projects were projects completed with a cost increase between 5% and 20%. High overrun projects were completed at cost increases of more than 20%. These thresholds of cost overrun levels were determined by a literature review and through interviews with field practitioners as described in the previous chapter.

### 4.4.1 Source of Cost Overruns Including Project Types

Previous efforts applying ensemble methods indicated that the prediction accuracy could be improved, however, lack of available input data still hampered prediction performance. More insight is needed into the meaning of input data since the ensemble learning method is in the earlier stages of being applied to the construction cost prediction area. Project cost overruns are caused by numerous reasons during the construction phase. In the bidding stage, influential factors on cost overruns are generated by a combination of project characteristics according to temporal priority, and these influential factors can be categorized into bidding characteristics. Bidding characteristics are affected by project characteristics. These two kinds of properties are addressed as critical contributors to project cost overruns in most studies. Williams (2002) found specific bidding patterns that produce cost overruns during the construction phase with a hybrid model using a regression model prediction

and a neural network. Moon (2015) studied cost increases and change orders (i.e., cost overruns) in DB and DBB delivery system projects using a statistical path analysis of projects in Korea. Cost increases in both DB and DBB projects were found to be significantly influenced by the ratio of the winning bid price to the owner's pre-bid estimate. Projects where significant differences existed between the low bid and the owner's pre-bid estimate had higher cost overruns. Moon also found that cost performance differed between different project types (e.g., civil and building construction).

Rosmond (1984) found that increasing the level of competition causes excessive cost overruns. Jahren and Ashe (1990) indicated four main factors that influence cost overruns: project size, project type, bid price to estimate ratio, and the level of competition. Williams (2005) studied the nature of the bid ratio and how it can describe the pattern of submitted bids associated with final project cost increases. Additionally, the study postulated that a bidder where the low bid is much lower than the other bids will seek to recoup losses through increasing change orders. Kuprenas (2005) employed regression analysis, and found that bidding characteristics, including bid price and the level of competition, correlate with cost performance. Gkritza and Labi (2008) applied econometric models to analyze highway project cost overruns. They found that for a given project type and duration, contracts with a larger size or with longer duration are generally more likely to incur cost overruns.

EI Wardani et al. (2006) considered different procurement methods, including sole source, qualification basis, the best value, and low-bid selection. Each type of DB project was compared in terms of cost, time, and quality of performance. They found that cost increases were the highest for competitive bidding, which was consistent with the results obtained by Moon (2015). Chen et al. (2016) studied the relationship of project characteristics with performance levels, including procurement methods, etc. These studies indicate that bidding characteristics are influenced by project characteristics.

Potentially, knowledge of project characteristics (i.e., the delivery method, project type, and project duration) combined with other factors generated in the bidding stage (i.e., procurement method, the ratio of a low bid to the owner's pre-bid estimate, and level of competition) can be used to enhance predictions of project performance. Also, previous studies imply that not only domain knowledge (e.g., construction project characteristics and bidding properties) but also modeling techniques should be combined to enhance predictions of project performance.

### 4.4.2 Selection of Input Data

This and the following subsections describe how input variables were selected and measured, and how the variables were interpreted in the context of the ensemble modeling results. The input data were derived from the collected database (field project work data) and an extensive literature review. Some of the existing research studies have identified factors that contribute to increases in construction costs. Williams et al. (1999) showed that a strong linear relationship exists between the natural logarithm of a low bid and that of the completed cost for highway projects in Great Britain and the United States. Skitmore and Ng (2003) developed different forms of regression models to forecast the actual construction cost and time; they found that the client sector, contractor-selection method, contractual arrangement, and project type could affect the final cost and time. Gkritza and Labi (2008) applied econometric models to the analysis of highway project cost overruns. They found that for a given project type and project duration, larger contracts or those with longer duration were generally more likely to incur cost overruns.

The previous researchers selected different numbers of input variables, between 1 and 64, which is a wide range. This research assumed the reason was that the number of input variables varies depending on the dataset that

researchers could collect. The underlined text in Table 4.9 shows common variables that are utilized both in previous studies and the collected database. The input data were selected from the list in Table 4.9, and categorized into two classes of characteristics (project types and bidding characteristics) in Table 4.10.

**Table 4.9** Input data used derived by literature survey

| Researcher | Project type (sample size) | Input data |
|---|---|---|
| Jahren and Ashe 1990 | Naval facilities (US, 1576) | Project size, the difference between the low bid and government estimate, the type of construction, and the level of competition |
| Williams et al. 1999 | Highway (UK, 28, US, 90) | Low bid |
| Williams 2002; 2005 | Highway (NJ, 302); Highway (TX, 1260) | Low bid, median bid, expected project duration, and number of bids |
| Attalla and Hegazy 2003 | Reconstruction project (Canada, 50) | 36 variables (scope definition and planning, tendering stage, schedule, cost, quality, and communication, safety) |
| Skidmore and Ng 2003 | Australian construction projects (various,93) | Client sector, contractor selection method, contractual arrangement, and project type |
| Ling et al. 2004 | Residential (Singapore,87) | 59 variables, delivery methods (DB/DBB) |
| George et al. 2005 | Industrial construction projects (US, 50) | 25 variables (project size, contract type, relative level of complexity, site conditions, and design schedule) |
| Gkritza and Labi 2008 | Highway (Indiana, 1957) | Project type, project duration, and contract size |
| Son et al. 2012 | Commercial buildings (84) | 64 variables (pre-project planning stage: project type, project size, and project duration) |
| Williams and Gong 2014 | Highway (California,1221) | Low bid, the completed project cost, and the number of bidders |
| Sousa et al. 2014 | Sanitation (Chicago,180) | Delivery method (DBB), and project type (water/ sewer) |

**Table 4.10** Input data for the ensemble learning model

| Characteristic | Input data |
|---|---|
| Project characteristics | Project delivery system (DB, DBB)<br>Project type as defined by two variables (described in Table 4.10)<br>Project duration (initial schedule in days) |
| Bidding characteristics | Bid to estimate ratio: ratio of the bid price to the owner's pre-bid estimate<br>Selected bid amount<br>Award method (qualification-based award or award to the lowest bidder)<br>Number of bidders (i.e., level of competition)<br>Number of companies forming a joint venture to construct the project |

***Input Data Descriptions***

According to the list in Table 4.10, the input variables are described as follows:

(1) Project delivery system

PDS is defined as the procurement method which includes the project scope, organizational structure, contract method, and award method (Gordon 1994). Previous studies show that PDS is a major contributor to project cost overruns (Ling et al. 2004; Sousa et al. 2014.). Presumably, the delivery method is a major factor in determining whether there will be project cost overruns. The type of scale for this variable is categorical.

(2) Project type

The data available for the projects included two variables that describe the type of projects being constructed. Table 4.11 lists the project type variables. Project type variable-1 is a general project type, and Project type variable-2 is a sub-category of the general project type. Nine project classifications were identified and categorized into these two levels of project types. Previous studies indicate that project type is one of the major factors that leads to cost overruns during the construction phase (Jahren and Ashe 1990; Konchar and Sanvido 1998; Love 2002; Gkritza and Labi 2008; Asmar et al. 2013; Shrestha et al. 2013; Chen et al. 2016; Liu et al. 2016).

**Table 4.11** Project type variables

| Project type variable-1 | Project type variable-2 |
|---|---|
| Civil | Sewerage |
| | Subway |
| | Road |
| | River |
| | Water supply |
| Building | Public building |
| | Residential building |
| Mechanical Facility | Mechanical facility |
| Landscaping | Landscaping |

(3) Project duration (initial schedule in days)

Previous studies have indicated that a strong relationship exists between project duration and cost (Rowland 1981; Gkritza and Labi 2008; Elfaki et al. 2014). The value was measured as the days that were set aside for the project in the preconstruction phase. The planned construction period was used for the project duration.

(4) Bid to estimate ratio (Selected bid amount)

This variable represents the difference between the contract amount and the engineer's estimate (i.e., the owner's pre-bid amount). This research considered the contract amount as a selected bid amount. Previous studies indicate that the bid to estimate ratio is a major factor in cost overruns (Rosemond 1984; Jahren and Ashe 1990). The type of scale for this variable is continuous.

(5) Award method (Procurement method)

The award methods considered were qualifications-based and low bid selection. The qualifications-based selection is generally used in DB and low bid selection is generally used in DBB (Molenaar et al. 2004; Chen et al. 2016). Sometimes, low-bid procured projects are used in the DB system (EI Wardani et al. 2006). In the current dataset, both methods were used in DBB and the qualifications-based method was used in DB projects.

(6) Number of bidders (Level of competition)

A number of previous studies found that this variable is a significant factor in cost overruns (Bhargava et al. 2010; Bordat et al. 2004; Jahren and Ashe 1990). This variable was measured by the number of bidders who submitted a bid to each project. The more competition, the higher the cost overruns.

(7) Number of joint ventures

This variable has been rarely considered in most existing studies due to the lack of data. This research considered the number of joint ventures as a contributing factor; the more joint ventures, the larger and more complicated the project, which leads to higher cost overruns. The value is measured by the number of companies forming a joint venture to bid on the project.

(8) Cost overruns

The terminology of cost overrun can mean cost changes, growth, variance, escalation, deviation, discrepancies between initial and final contract amount (actual as-built cost). In the current model, the operational definition of cost overrun was defined as a percentage cost growth (i.e., cost overrun rate).

(9) Cost overrun levels

As previously discussed, the thresholds of the cost overrun levels were determined through literature review and experts' interviews as described in

the preliminary section. In this model, the cost overruns were classified into near/under, medium, and high. The values were less than 5%, between 5% and 20%, and more than 20%, respectively. The model produced a prediction of the level of cost overruns that would occur during the construction phase.

### 4.4.3 Results

The ensemble model validation was conducted by comparing conventional single-learning models wth the 10-fold cross-validation based on three performance metrics (i.e., prediction accuracy, precision, and recall). K-Star (i.e., KNN) and Ripple-Down as the representative instance-based and rule-based machine learning algorithms, respectively, were employed for the single-learning model. The outputs of the models represented the level of overruns based on accuracy, precision, and recall.

Table 4.12 presents of the predictions performed by each model using the RapidMiner environment. To provide a more rigorous test of the relationships between the input variables and cost overruns, five runs were performed using different random number seeds to select the members of the 10 groups of cases. The average accuracies of each model ranged from 55.19% to 61.41%. The

stacking ensemble yielded the best accuracy, although the accuracy was 61.41%, which was not much higher. The table also lists the precision and recall for the prediction of the three levels of cost overruns.

**Table 4.12** Comparison of single-learning models and stacking ensemble model predictions

| Model type | Accuracy | Class precision | | | Class recall | | |
|---|---|---|---|---|---|---|---|
| | | High overrun | Medium | Near/ under | High overrun | Medium | Near/ under |
| Ripple-Down | 55.19% | 58.24% | 54.72% | 35.64% | 61.54% | 64.10% | 23.45% |
| K-Star | 57.23% | 56.32% | 61.42% | 55.76% | 42.76% | 68.89% | 45.42% |
| Stacking ensemble | 61.41% | 61.66% | 62.97% | 52.85% | 64.90% | 70.28% | 31.71% |

Table 4.13 shows the detailed stacking model results for the five model runs. The model yielded an average accuracy of 61.41%. The lowest prediction accuracy in the five runs was 59.88%, and the highest was 63.26%. Table 4.13 also lists the precision and recall for the prediction of the three levels of cost overruns. The precision of the prediction represents the percentage accuracy of the model's prediction, while the prediction recall represents the percentage of correctly predicted cost overrun levels.

**Table 4.13** Detailed ensemble model runs when project-type variables are included in the input data

| Run | Accuracy | Class precision | | | Class recall | | |
|---|---|---|---|---|---|---|---|
| | | High overrun | Medium | Near/ under | High overrun | Medium | Near/ under |
| 1 | 63.26% | 63.53% | 64.96% | 56.00% | 66.67% | 72.38% | 34.15% |
| 2 | 60.26% | 59.55% | 63.16% | 50.00% | 63.86% | 68.57% | 31.71% |
| 3 | 62.02% | 62.65% | 62.06% | 56.52% | 62.65% | 73.33% | 31.71% |
| 4 | 61.64% | 62.35% | 63.48% | 51.72% | 63.86% | 69.52% | 36.59% |
| 5 | 59.88% | 60.22% | 61.21% | 50.00% | 67.47% | 67.62% | 24.39% |
| Average | 61.41% | 61.66% | 62.97% | 52.85% | 64.90% | 70.28% | 31.71% |

The results of Table 4.13 indicates that the model was able to predict high and medium overruns with relatively good precision and recall while predicting projects delivered near or under the original bid amount with significantly lower precision and recall.

Table 4.14 lists the confusion matrix for ensemble model Run1 which presents the most accurate stacking run. The confusion matrix displays the number of correct and incorrect predictions made by the model compared with the actual classifications in the test data. The matrix size is n × n, where n represents the three levels of cost overruns.

**Table 4.14** Confusion matrix for model run 1

| | True high overrun | True medium | True near /under | Class precision |
|---|---|---|---|---|
| Prediction of high overrun | 54 | 21 | 10 | 63.53 % |
| Prediction of medium | 24 | 76 | 17 | 64.96% |
| Prediction of near/under | 3 | 8 | 14 | 56.00% |
| Class recall | 66.67% | 72.38% | 34.15% | |

To obtain better insight into the explanatory variables, the importance of project type on the accuracy of predictions of the project cost overruns was tested. Additional runs were made without the input of the two project-type variables. The groupings of the projects for cross-validation were the same as for the previous set of runs.

Table 4.15 presents the predictions made when the project-type variables were withheld from the input data. An examination of Table 4.15 indicates that the accuracy of the predictions was lower, especially the average class recall for projects completed at near/under the original bid of 9.15%, which was significantly low.

**Table 4.15** Predictions made when project-type variables were withheld from the input data

| Run | Accuracy | Class precision | | | Class recall | | |
|---|---|---|---|---|---|---|---|
| | | High overrun | Medium | Near/ under | High overrun | Medium | Near/ under |
| 1 | 54.62% | 61.11% | 52.35% | 60.00% | 39.76% | 84.76% | 7.32% |
| 2 | 55.02% | 61.70% | 53.22% | 54.55% | 34.94% | 86.67% | 14.63% |
| 3 | 52.37% | 55.56% | 52.41% | 33.33% | 36.14% | 82.86% | 7.32% |
| 4 | 55.10% | 62.75% | 53.22% | 42.86% | 38.55% | 86.67% | 7.32% |
| Average | 54.28% | 60.28% | 52.80% | 47.69% | 37.35% | 85.24% | 9.15% |

### 4.4.4 Discussions

The analysis of the project data indicates that project type is an important factor that influences cost overruns. The approach to explaining the phenomenon of project cost overruns is to identify a key predictor to obtain better prediction results. The project type was found to be an important factor during the input data selection process, which was tested using a stacking ensemble learning model. The prediction results were much poorer when the project type variables were withheld from the input data, which indicates that the type of facility being built is a major factor in the level of cost overruns. Clearly, some project types are more difficult to build than others. The results provide a theoretical basis to support that the project type should be controlled before conducting research on cost overruns. More specifically, practitioners and researchers should estimate, predict, or evaluate project cost overruns associated with project types, so they can manage risk according to project types.

***Prediction Accuracy Issue***

Most prediction models have estimated construction project costs in the planning phase to prepare bids, and they have yielded higher accuracy. Providing an exact numerical value for a cost prediction is critical in the

planning phase because the practitioners need to know the exact value to prepare the bid or estimate the costs. However, as Arditi and Tokdemir 1999 mentioned, the cost prediction related to the construction industry may never be predicted with 100% accuracy because all influential factors (e.g., uncertainties, economic situation, and environmental factors) cannot be considered. Further, this study predicts the project cost overrun in the bidding stage which is a different phase from the planning phase.

As mentioned in the Introduction, two major features of past work on the poor accuracy of prediction in the bidding stage are insufficient data and limited state-of-the-art techniques for the predicting cost overrun model. The available empirical input data for the cost overrun prediction in the bidding stage are very limited compared to well-defined planning stage data. For example, the prediction model in the planning phase utilizes well-defined design factors (e.g., gross floor area, number of floors, number of elevators, height between stories, depth of pit, roof type, hallway type, structure type, and so forth), subsequently, the prediction accuracies are higher than that for the prediction model using bidding stage data (e.g., bidding characteristics: award method, number of bidders, winning bid amount, bid to estimate rate).

A previous study, which is based on the same project phase (i.e., bidding stage), and the stacking ensemble model yielded an average accuracy of 43.72%

for the same number of model runs (Williams and Gong 2014). The average accuracy of 61.41% of this study shows the improvement in prediction accuracy compared to the previous study. The difference between the two studies stems from the available empirical data. Most previous studies related to bidding stage prediction used only bidding characteristics (e.g., bid price, the number of bidders) (Williams et al. 1999; Williams 2002, 2005, 2007; Williams and Gong 2014). However, this study used bidding characteristics combined with project characteristics, which led to an improvement in the prediction accuracy. This research indicates that the prediction accuracy can be improved by adding more information. In addition, the importance of this model is in preventing risk in the bidding stage by understanding how each input variable plays a role, sometimes in combination or by influencing each other to cause cost overruns in any project phase.

## 4.5 Summary

This chapter described how this study developed, validated and verified a moderation effect analysis model to examine project type moderates the effect of PDS on cost performance under what circumstances.

In the moderation model development process, a conceptual and statistical moderation model was established to test Hypothesis 1. Variables were defined for the moderation analysis. Data were then collected and analyzed, and the attributes of the variables were explored using data analysis. The variables were DB and DBB project delivery systems, cost growth as a performance metric, and project type. Descriptive statistics of variables were presented.

For validation and verification of the moderation model, a two-way ANOVA was conducted to examine the moderation effect of two project types: residential and public buildings. Since the interaction effect of PDS and project type was statistically significant, Hypothesis 1 was confirmed. Through the visualization of moderation, the main effect of PDS did not appear consistently, and other results appeared to depend on mutual combinations with project types. This result confirmed that the effect of PDS on cost performance differs depending on project type.

In addition to the model validation, multi-group analysis and ensemble stacking learning were conducted to verify the moderation model. The multi-group analysis was also used in the mediation analysis model, and this chapter explained that the coefficients were assumed to be the same across project types using different datasets (building and civil projects) in the validation model. The results revealed that the cost performance of PDS depends on project type and supports future research that analyzes the cost performance of PDS, distinguished by project types. The results of the ensemble-learning prediction model yielded overall accuracy between 59.88% and 63.26% for five test runs. The best predictions were found for projects that incurred big and medium overruns. Information about the project type being constructed was shown to be an important contributor to the accuracy of the predictions. When these data were withheld from the model input, the accuracy was lower; in particular, very low accuracy was realized for the prediction of projects with low or negative cost increases.

# Chapter 5

# Mediation Model

This chapter describes the development and validation of a mediation effect analysis model that explores the causal relationship between PDS and cost performance using the path analysis method. In the mediation model development process, the model framework was established, and the variables and theoretical path model were defined. In the model validation process, the effects of PDS on cost performance were identified and quantified through three experimental steps.

## 5.1 Model Development

### 5.1.1 Structure of Mediation Model

The structure of the path analysis model is depicted in Figure 5.1. The model was developed and tested as follows: a theoretical path model was established based on a literature review in order to test Hypothesis 2. Subsequently, data were collected according to the theoretical model and analyzed, and the model fit was assessed to select the path model from among

the postulated alternatives (i.e., path diagrams). Then, a multi-group analysis was conducted to examine the statistical significance of the effect of project types, and both the direct and indirect effects of PDS on cost growth were tested using the bootstrap method. Finally, the distinguished effects of PDS were identified and quantified for the comparison of DB and DBB systems.

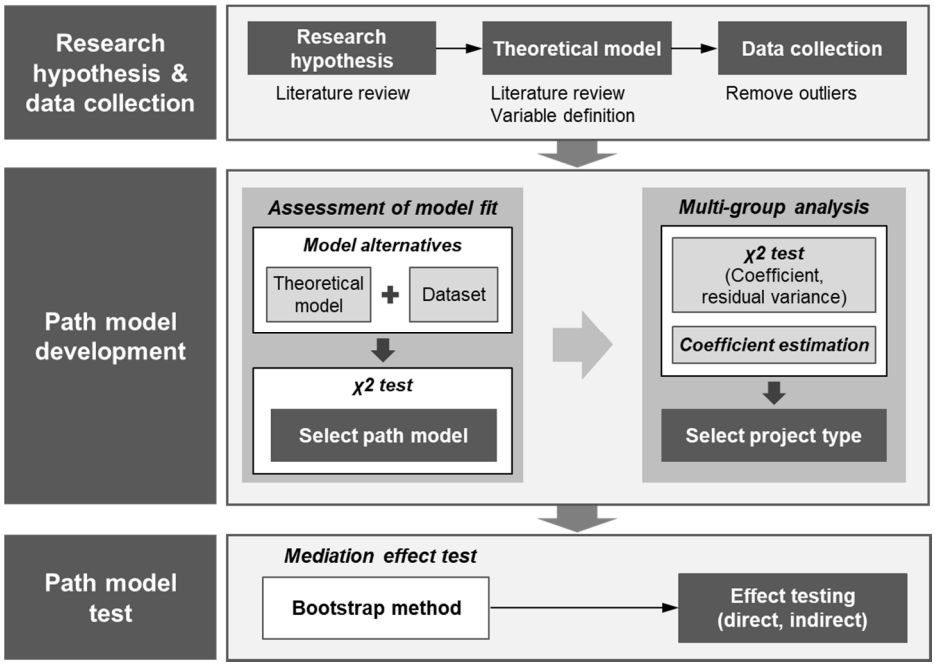



**Figure 5.1** Structure of the path analysis model

### 5.1.2 Causal Chain of Project Delivery Systems

To build a theoretical path model, model variables needed to be designed first. The list of model variables was derived from the literature review presented in the previous section, and then defined as follows, presented here in chronological order. Each variable belonged to one of the phases in the project life cycle, such as the planning, procurement, or construction phase.

Figure 5.2 depicts the theoretical mediation model, integrating the variables listed into Moon's (2015) model, which identified a mediator effect of bid price on the relationship between PDS and cost performance. First, the variable "number of bidders" was added to Moon's model, and then bid price and the number of bidders were categorized as bidding characteristics. Next, the bidding characteristics were assumed to be related to the contractors' interests—a tendency to increase profitability using cost growth.

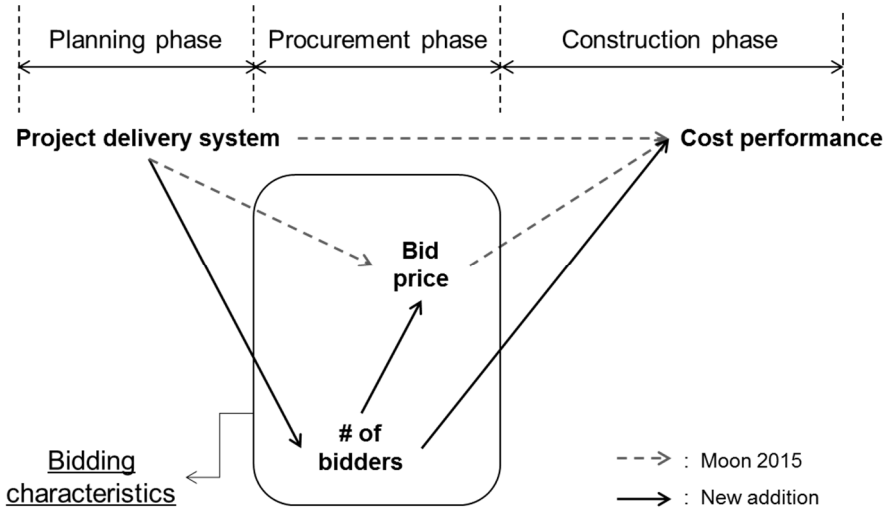



**Figure 5.2** Theoretical mediation model

***Variable Definitions***

The variables for the theoretical model were designed prior to data collection. The selected variables were derived from the literature review presented earlier and were defined as follows. Each variable belonged to one of the project life cycle phases (i.e., the planning, procurement, or construction phase) and was defined by temporal priority (Hume 1938).

First, the PDS was identified as a variable in the project planning phase. Subsequently, bid price and the level of competition (i.e., number of bidders) were categorized as bidding characteristics and allocated during the

procurement phase. Finally, the cost growth variable was allocated during the construction phase. Based on the literature review, the bidding characteristics were assumed to be influenced by the PDS and, in turn, to influence cost growth.

As highlighted by Hume (1938) and Kline (2011), temporal priority is a necessary condition for causality, and PDS has a causal relationship with bidding characteristics. Therefore, the variable attributes for bidding characteristics was changed from independent to intervening due to its role as a mediator between PDS and cost growth. Table 5.1 depicts the conceptual definitions of the selected variables.

**Table 5.1** Conceptual definitions of variables for mediation model

| Name | Conceptual definition | Type of variable | Type of scale | |
|---|---|---|---|---|
| Project delivery system | The type of delivery system: DB and DBB | Independent | Dummy | Qualitative |
| Number of bidders | The number of bidders vying for a project representing the level of competition | *Intervening* | Ratio | Quantitative |
| Bid price | Bid to pre-bid estimate cost ratio (%) | *Intervening* | Ratio | Quantitative |
| Cost growth | Percentage growth from contract amount (%) | Dependent | Ratio | Quantitative |

Note: DB = design-build; DBB = design-bid-build.

As stated in the Data Collection and Analysis section, the cost growth variable was calculated by excluding price fluctuations from the final project cost to reduce the influence of exogenous factors. Previous studies mentioned that there was inconsistency among studies with how cost growth was measured and this could have led to inconsistent results in the comparison of DB and DBB (Goftar et al. 2014; Sullivan et al. 2017). The definition of cost growth variable in this study was the percentage difference between the initial contract project cost and the final project cost with the price fluctuation subtracted. The operational definitions of the variables were as follows:

- Project delivery system (PDS) (Eq. 4.1)

  DB = 0

  DBB = 1

- Cost growth (%) (Eq. 4.2)

$$= \frac{\text{Final project cost} - \text{Price fluctuation} - \text{Contract project cost}}{Contract\ project\ cost} \times 100$$

- Bid price (%) (Eq. 4.3)

$$= \frac{\text{Contract project cost}}{Owne's\ pre{-}bid\ estimate} \times 100$$

## 5.2 Model Validation

### 5.2.1 Data Descriptions

Through preliminary descriptive statistics in Chapter 3, building and civil projects were selected for the mediation analysis because they had similar distributions and provided a sufficient sample size for both DB and DBB systems. The dataset included 197 projects. DB and DBB projects were similarly distributed; DB comprised of 82 observations (41.6%) and DBB accounted for 115 observations (58.4%). Table 5.2 presents the frequencies of project types according to PDS.

**Table 5.2** Frequencies of project types according to PDS

| Project type (group) | Total (%) | DB | DBB | Project type (subgroup) | Sub-total | DB | DBB |
|---|---|---|---|---|---|---|---|
| Building | 90(45.7) | 34 | 56 | Public building | 49 | 23 | 26 |
| | | | | Residential building | 41 | 11 | 30 |
| Civil | 107(54.3) | 48 | 59 | Sewerage | 8 | 0 | 8 |
| | | | | Subway | 32 | 32 | 0 |
| | | | | Road | 44 | 9 | 35 |
| | | | | River | 5 | 3 | 2 |
| | | | | Water Supply | 18 | 4 | 14 |
| Total | 197(100.0) | 82(41.6) | 115(58.4) | | 197 | 82 | 115 |

Note: DB = design-build; DBB = design-bid-build

To manage the missing values in the dataset, the full information maximum likelihood (FIML) method was used (Xiong et al. 2015). Several methodologists recommend FIML because it provides an unbiased estimation even when the missing mechanism is missing a part at random as well as missing something completely at random (Enders 2001; Enders and Bandalos 2001).

### 5.2.2 Path Diagram Alternatives and Model Fit Assessment

The process models for how PDS affects cost performance were postulated based on the literature survey (i.e., path model alternatives). Figure 5.3 depicts path diagrams for two alternative mediation models. In Figure 5.3(a), PDS has a direct effect on cost growth; further, it has some indirect effects meditated by the number of bidders and bid price. In Figure 5.3(b), PDS has both direct and indirect effects on cost growth; however, the indirect effects have different paths. Although the number of bidders was assumed to have no direct effect on cost growth, it did have an indirect effect mediated by the bid price. While some research has examined the effect of the number of bidders on cost growth (Kuprenas 2005; Gkritza and Labi 2008), the current research provided statistical evidence that the effect can be explained using the causal effect model.

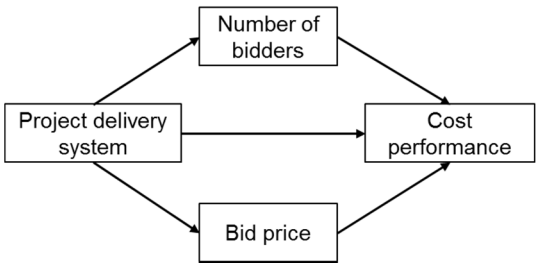



**Figure 5.3 (a)** Path model-1

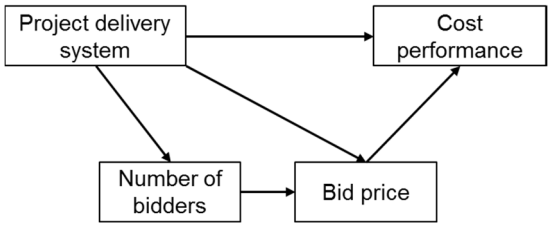



**Figure 5.3 (b)** Path model-2

The first step in testing a path analysis model was to check model fitness before the interpretation of any coefficients (Loehlin 1998; Kline 2011). The fit of both path models 1 and 2 was examined to determine the validity of the proposed models. Since the proposed models were only one parameter short of being saturated models per group, the Chi-square ($\chi^2$) test was used to determine whether the coefficient could be assumed to be zero.

The scaled $\chi^2$ test (Satorra and Bentler 2001) for the first model versus the saturated model rejected the null hypothesis (scaled $\chi^2$ difference = 14.695,

degree of freedom (*df*) = 2, *p*-value = 0.001), that is, the first model did not adequately fit the data. The scaled $\chi^2$ test of the second model presented a scaled $\chi^2$ difference of 0.807 with *df* of 2 and a *p*-value of 0.668, indicating that the second model did adequately fit the data (Table 5.3).

**Table 5.3** Test result of Chi-square for the path diagram model fit

| Model Fitness | Path model-1 | Path model-2 |
|---|---|---|
| $\chi^2$ difference | 14.695 | 0.807 |
| *df* | 2 | 2 |
| *P*-value | 0.001 | 0.668 |
| Significant | Yes | No |

Note: *df* = degree of freedom; $\chi^2$ = Chi-square

Therefore, the second model (i.e., path model-2) was used to estimate the effects of PDS. The fit of the second model was adequate with the following values: scaled $\chi^2$ *p*-value = 0.668, root-mean-square error (RMSE) = 0.000 (0.00–0.207), comparative fit index (CFI) = 1.000, and *p*-value for root-mean-square error of approximation (RMSEA) = 0.639 (Browne and Cudeck 1992).

For the methods of this approach, even though the model showed that it was an adequate fit, nobody can be sure whether the model is true to reality. As Bollen (1989) mentioned, researchers can only say their causal model is

consistent with the data in hand and that there may be other models that show better model fits for different datasets. For instance, causal relations can be nonlinear or there might be confounding variables in the causal relationships hypothesized.

### 5.2.3 Selecting Project Type (Multi-Group Analysis)

Following the model fit assessment, multi-group analysis was conducted to examine the statistical significance of the project types. Based on the moderation model verification in Section 4.3.3, the data were analyzed using path model-2 with different coefficients and different residual variances for each project type. Following the scaled $\chi^2$ test, coefficient estimations were used to examine the significance of each path on the path model according to project types. The variables for the significance test is listed in Table 5.4.

**Table 5.4** Variables for the significance test of selecting project type

| Variable Name | Type of variable | Variable description |
|---|---|---|
| X | Independent | Project delivery system |
| Y | Dependent | Cost growth |
| M1 | Intervening (mediator) | Number of bidders |
| M2 | Intervening (mediator) | Bid price |

The coefficients of civil and building projects for path model-2 were estimated as shown in Tables 5.5 and 5.6, respectively. In the tables, *X* and *Y* are independent and dependent variables, respectively, whereas *M1* and *M2* are mediators. Each path is the same as the direct effect among variables. Based on this result, the significant project type for the path analysis was selected.

**Table 5.5** Estimated coefficients for civil projects

| Antecedent | Consequent | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | M1 | | | M2 | | | Y | | |
| | Coeff. | S.E. | *p*-value | Coeff. | S.E. | *p*-value | Coeff. | S.E. | *p*-value |
| X | 70.65 | 10.76 | 0.00 | -10.95 | 1.56 | 0.00 | 11.48 | 5.65 | 0.04 |
| M1 | | | | 0.01 | 0.01 | 0.69 | | | |
| M2 | | | | | | | 0.04 | 0.33 | 0.90 |
| Constant | -68.25 | 10.76 | 0.00 | 103.13 | 2.50 | 0.00 | -11.40 | 35.04 | 0.75 |
| | $R^2$ = 0.306 | | | $R^2$ = 0.443 | | | $R^2$ = 0.088 | | |

Note: Coeff. = coefficient; S.E. = standard error; $R^2$ = coefficient of determination.

**Table 5.6** Estimated coefficients for building projects

| Antecedent | Consequent | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | M1 | | | M2 | | | Y | | |
| | Coeff. | S.E. | *p*-value | Coeff. | S.E. | *p*-value | Coeff. | S.E. | *p*-value |
| X | 69.83 | 12.60 | 0.00 | -16.18 | 1.44 | 0.00 | -0.07 | 3.58 | 0.98 |
| M1 | | | | 0.02 | 0.01 | 0.00 | | | |
| M2 | | | | | | | -0.44 | 0.21 | 0.04 |
| Constant | -67.13 | 12.61 | 0.00 | 110.21 | 2.11 | 0.00 | 49.28 | 22.65 | 0.03 |
| | $R^2$ = 0.187 | | | $R^2$ = 0.613 | | | $R^2$ = 0.1 | | |

Note: Coeff. = coefficient; S.E. = standard error; $R^2$ = coefficient of determination

For civil projects, the direct effect of the number of bidders on the bid price, and the direct effect of bid price on cost growth, were not statistically significant, whereas PDS had statistically significant direct effects on the number of bidders, bid price, and cost growth. Overall, the number of bidders and bid price ($R^2$ = 0.088) could not successfully explain cost growth. In building projects, the direct effect of PDS on cost growth was not significant, however, the direct effects of the other variables were statistically significant.

In the results for both civil and building projects, PDS had statistically significant effects on the number of bidders and bid price. The difference between civil and building projects was reflected in the effect of bid price on cost growth. Since the paths through bid price on cost growth showed the effects to be statistically insignificant for civil projects, these projects were excluded, and building projects were selected as the project type for the path model analysis.

### 5.2.4 Identifying Effects of PDS on Cost Performance

Following the multi-group analysis, both the direct and indirect effects of PDS on cost growth for building projects were examined using the bootstrapping method. This method allows for the identification and quantification of the effects of PDS on cost performance to enhance the comparison of DB and DBB delivery systems. If the direct effect of PDS on cost growth is significant, then the PDS with lower cost growth is superior to all other PDSs, which is the same conclusion arrived at by previous studies. However, if the indirect effect of PDS on cost growth is significant, then it is not certain that the given PDS outperforms the other PDSs despite having lower cost growth. Accordingly, under certain conditions, the approaches used in previous studies may result in inaccurate comparisons of the cost performances of DB and DBB systems.

In this path model, an indirect effect comprised more than two paths. Table 5.7 presents the test results. The third column (titled Estimate) shows the estimated coefficients and the .95 confidence intervals obtained from bootstrapping. The values shown in the fourth (S.E.) and fifth (*p*-value) columns are the results based on a normal theory (used only as a reference). The total effect of PDS on cost growth is statistically significant and the estimate presented is quite large (6.24 with a confidence interval of 2.05–10.85).

Also, both the specific indirect effects of PDS on cost growth are shown to be statistically significant. In particular, the indirect effect mediated by bid price is significant and the estimate is large (7.04 with a confidence interval of 1.15–14.52). Since the direct effect of PDS on cost growth was not statistically significant and the other indirect effects were statistically significant, these results showed a complete mediation effect. Therefore, in the case of building projects using the DBB system, the complete mediation effect was examined for statistical significance and Hypothesis 2 was supported.

**Table 5.7** Effects of PDS on cost growth via different paths for building projects

| Effect | Path | Estimate (Bootstrap confidence interval) | S.E. | *p*-value | Standardized value |
|---|---|---|---|---|---|
| Specific indirect | PDS → number of bidders → bid price → cost growth | -0.72 (-1.66 ~ -0.11) | 0.41 | 0.078 | -0.065 |
| Specific indirect | PDS → bid price → cost growth | 7.04 (1.15 ~ 14.52) | 3.46 | 0.042 | 0.634 |
| Direct | PDS → cost growth | -0.074 (-7.50 ~ 6.69) | 3.58 | 0.984 | -0.007 |
| Total | Sum of the above | 6.24 (2.05 ~ 10.85) | 2.27 | 0.006 | 0.563 |

Note: PDS = project delivery system; S.E. = standard error.

The model was found to be reliable. In particular, the causal effect of PDS on cost growth mediated by bid price was reliable, although other insignificant effects should be investigated using different data, as per Bollen (1989). For instance, causal relationships can be nonlinear, or there might be confounding variables that have been omitted from the causal relationships hypothesized in this research. Although the model hypothesized causal relationships of bidding characteristics between PDS and cost growth, the variables could have been influenced by other factors that were not considered by the research.

## 5.3 Summary

This chapter elaborated on the mediation effect analysis model used in this study to identify and quantify the effects of PDS on cost performance using the path analysis method. The model development and validation were described.

In the mediation model development process, the model framework for the path analysis was established. The causal chain of PDS on cost performance was described through a theoretical path model that was built based on the literature review to test Hypothesis 2. Prior to the theoretical model, variables were designed and defined, specifically conceptual and operational definitions of variables for the mediation analysis.

In the model validation process, the effects of PDS on cost performance were identified and quantified through three experimental steps. First, path diagram alternatives were postulated and path model-2 was selected using the model fit assessment. Second, the test of statistical significance of project types showed that building projects were significant for the path model. Finally, through the bootstrapping method, the effects of PDS were examined.

Each PDS (i.e., DB and DBB delivery systems) that increased cost growth varied based on project type. Since the direct effects of both PDSs were not statistically significant, and the indirect effects of the DBB system for building projects were significant, this demonstrated the full mediation effect of bidding characteristics. These results enhanced the comparison of cost performance between DB and DBB delivery systems discussed in the following chapter.

# Chapter 6

# Comparing Cost Performance of DB and DBB: Moderation and Mediation Applications

This chapter compares the cost performance of DB and DBB delivery systems using the moderation and mediation effects analyzed in the previous two chapters. Applying those effects to the comparison, this chapter compares DB and DBB based on third factors (i.e., project type, bidding characteristics) that affect cost performance. At the end of the chapter, practical applications are discussed.

## 6.1 Comparison by Project types

An independent samples *t*-test with two tails was performed to verify whether the mean value difference in cost growth between DB and DBB building and civil projects was statistically significant or not. For public building projects, the mean value and standard deviation (SD) of cost growth were calculated for DB (mean = 7.587, SD = 7.914) and DBB (mean = 14.485, SD = 11.283) building projects. The variances in cost growth for the DB and DBB projects were roughly equal; the significance level of Levene's test had a

*p*-value of .250 (> .05). The mean difference in cost growth between DB and DBB was found to be statistically significant (t = -3.126, *p*-value = .002 (≤ .05), mean difference = 6.898 percentage point (pp)) at a confidence level of 95% (*p*-value = 0.05).

For the civil infrastructure projects, the mean difference in cost growth between DB and DBB was not statistically significant (*t* = -.909, *p*-value = .365 [> .05], mean difference = 3.690pp) at a confidence level of 95%. Table 6.1 presents the test results.

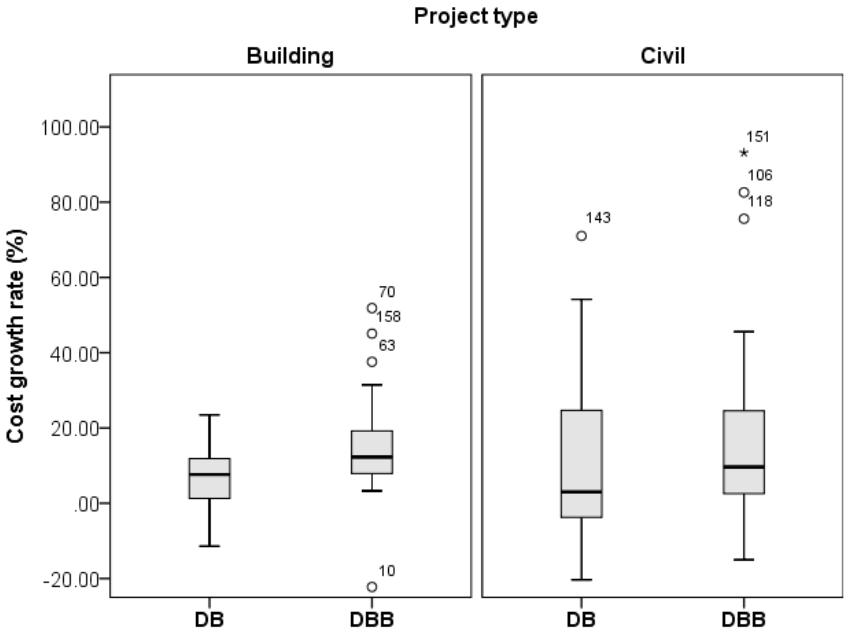
**Table 6.1** Independent samples *t*-test for cost growth mean differences between DB and DBB

| Dependent variable | Project type | PDS | N | Mean (%) | SD | Mean difference (%) | *t*-statistic | *p*-value |
|---|---|---|---|---|---|---|---|---|
| Cost growth (%) | Building | DB | 34 | 7.587 | 7.914 | 6.898pp DB less | -3.126 | 0.002 |
| | | DBB | 56 | 14.485 | 11.283 | | | |
| | | Sub-total | 90 (45.7%) | | | | | |
| | Civil | DB | 48 | 11.713 | 20.285 | 3.690pp DB less | -0.910 | 0.365 |
| | | DBB | 59 | 15.403 | 21.330 | | | |
| | | Sub-total | 107 (54.3%) | | | | | |

Note: PDS = project delivery system; DB = design-build; DBB = design-bid-build; SD = standard deviation

According to the *t*-test results (i.e., the traditional approach), the cost growth of DB for civil projects was 3.690 pp lower than that of DBB; however, the test was not found to be statistically significant. Consistent with the results of previous studies using descriptive statistics (Molenaar et al. 1999; Ibbs et al. 2003; Warne 2005), the evidence indicates that the DB system for civil projects is superior to the DBB system.

Additionally, box plots were generated to visualize cost growth differences between DB and DBB systems according to building and civil project types (Figure 6.1). Both project types indicate that the cost growth of DB is lower than that of DBB, which is consistent with the results presented in research over the last two decades (Goftar et al. 2014; Sullivan et al. 2017).




Note: DB = design-build; DBB = design-bid-build

**Figure 6.1** Box plot showing the change in cost growth rate according to PDS and project type

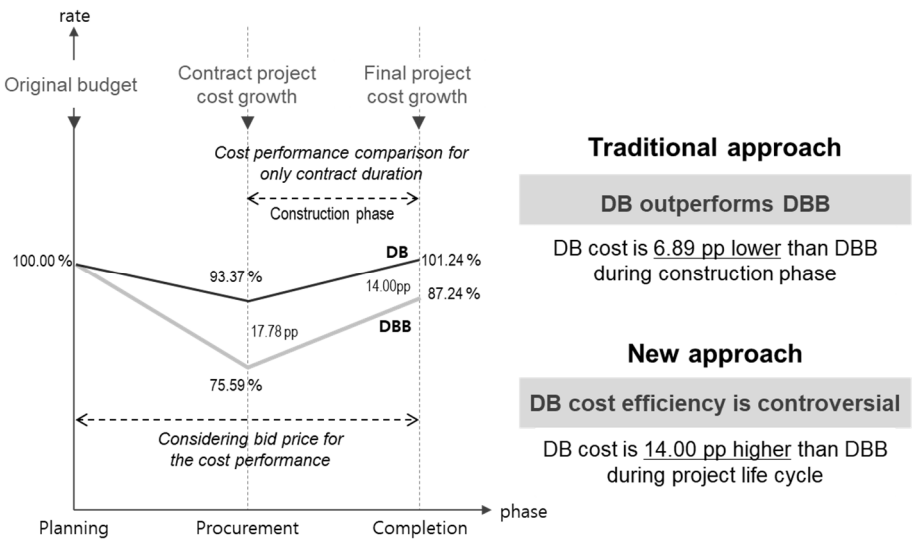
For the building project type, the cost growth of DB was 6.898 pp lower than that of DBB, that is, DB was superior to DBB when both were judged using a traditional approach. However, as Hypothesis 2 was confirmed, and the building projects incorporating a DBB system revealed that PDS is subject to mediation effects, the project owner should avoid the conclusion that DB outperforms DBB in every scenario. This is because cost performance is more likely to be influenced by bidding characteristics, rather than PDS. Therefore, the benefit of using DB as a project delivery strategy to save costs is debatable.

## 6.2 Comparison by Bidding Characteristics

The comparison of cost performance between the DB and DBB delivery systems in this research included an examination of the mean value difference of cost growth using a *t*-test to compare PDSs associated with project type (i.e., building and civil projects). The cost performance of DB and DBB systems for building and civil projects were examined using the mediation effect. The path model test results showed that the PDS had indirect effects on cost growth, which was mediated by bidding characteristics for building projects, but not for civil projects. Therefore, the traditional *t*-test method was used to compare the mean value differences for DB and DBB systems for civil projects, whereas the mediation effect and *t*-test were used to compare the differences in building projects. The dataset for this comparison model utilized the same dataset used for the mediation model described in Chapter 5.

Figure 6.2 describes the cost variance of each PDS during a project's life cycle. Based on bidding characteristics, the contract cost growth rates from the original budget (i.e., owner's pre-bid estimate) were 93.37% for DB and 75.59% for DBB projects. However, the final project cost growth rates were 101.24% for DB and 87.24% for DBB projects. Further, the mean difference in contract cost growth between DB and DBB was 17.78 pp, which was subsequently

changed to 14.00 pp at the completion phase. If the contract duration alone was considered to estimate DB's cost efficiency, then the construction cost growth of DB was 6.89 pp lower than that of DBB. However, in considering the total cost growth (i.e., final project cost as compared to the original project cost), DB showed 14.00 pp higher cost growth than DBB. Consequently, in this case, the cost savings associated with DB is controversial.

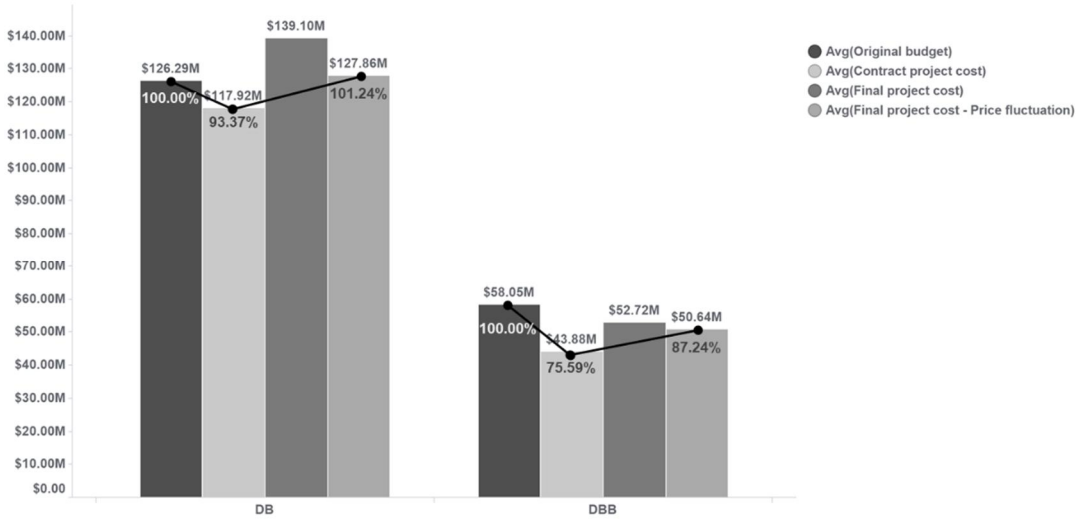



Note: DB = design-build; DBB = design-bid-build; pp = percentage point

**Figure 6.2** Changes in cost variance according to PDS for building projects (percentage value)

This outcome is also presented with actual cost values in Fig. 6.3. As mentioned in the Variable Definition section, the cost growth variable was

measured without price fluctuations to exclude economic situations that are considered to be exogenous factors. To confirm this assumption, the cost variance in the actual value over the project life cycle for each PDS is compared in Fig. 6.3. The bar chart shows the average value according to PDS in side-by-side bars: original budget, contract project cost, final project cost (as-built), and final project cost without the price fluctuations.




Note: DB = design-build; DBB = design-bid-build

**Figure 6.3** Changes in cost variance according to PDS for building projects (actual value)

Comparing the first bars (original budget) of each PDS with the second, and the fourth stands for the actual values of the percentages presented in Fig. 6.2. The third value of the DB projects shows imbalance when compared to the

original budget, as well as for DBB projects. Therefore, it could also enhance the cost performance comparison of DB and DBB for the price fluctuations to be withheld from the cost growth measurement.

## 6.3 Discussions

Ibbs et al. (2003) and Fernane (2011) argued that the reason that DB projects sometimes result in a higher cost change compared to DBB projects is that the former do not have a well-defined scope at the beginning of the project. Therefore, numerous studies have investigated the reason for the inconsistent comparison results with respect to project type, dataset, and other influential factors (Asmar et al. 2013; Chen et al. 2016). However, this research focused on the assumptions underlying low cost growth, which differentiates it from previous research. According to this research, lower cost growth should not always be assumed to indicate the superiority of one PDS over another.

Regarding bidding characteristics, in most cases, DBBs are likely to have a mediation effect on building projects since they facilitate a higher level of competition that affects bid price and cost growth during the construction phase. Conversely, DB projects record lower cost growth. Therefore, lower cost

growth should not always be considered a benchmark for better performance. To the best of the authors' knowledge, the current study is the first among PDS evaluation studies to have tested this issue hypothetically using an empirical comparison.

## 6.4 Practical Applications

***Specifying a Condition of Mediation Effects***

The results of this research can be generalized by specifying the conditions under which bidding characteristics (i.e., bid price and the level of competition) have a mediating effect on owner type (public/private), PDS (DB/DBB), and project type (building/civil infrastructure). For example, while evaluating or selecting a DBB delivery system for various types of public buildings in the city (e.g., residential, hospital, library, office, or community center), public-sector owners should consider the bidding characteristics that mediate the effect of PDS on cost performance.

Building projects typically involve more materials and more complicated types of work than civil projects and are hence comparatively less well-defined at the design-development stage. In addition, any further changes to the scope

of the building projects easily result in higher cost growth figures with the progress of the construction work. Shrestha et al. (2012) and Goftar et al. (2014) compared the literature from the previous two decades with a focus on project types, comparing the cost growth differential between DB and DBB for building (vertical construction) and highway (horizontal construction) project types. The difference between DB and DBB for building projects is much larger than that for highway projects; that is, building projects benefit more from DB than highways do. However, considering the mediation effect of bidding characteristics on DBB building projects, the results of previous studies do not seem conclusive.

***Adjusting Level of Project Type Category***

Additionally, previous efforts to categorize the project type into building and highway (Shrestha et al. 2012; Goftar et al. 2014) do not seem to match the classification level. The building project type includes different sub-project types (e.g., public university, high-performance building, residential building, library, and community center), whereas highway is a sub-project type (e.g., bridge, tunnel, rail road, and subway), which can have a higher level of classification (i.e., civil infrastructure project). Therefore, this research proposes a change in categorization from highway to civil infrastructure projects.

***Providing Theoretical Ground for Formulations of Cost Growth***

There is inconsistency among the studies on how cost growth was measured (Sullivan et al. 2017). These different methods include:

(a) Final cost against the awarded amount printed in the contract documents

(b) Final costs against the owner's pre-bid estimation by engineers

(c) A lack of details of the calculation

The results of the comparison according to bidding characteristics indicate that a project cost including bidding stage variance should be considered when bidding characteristics mediate the effects of PDS on cost performance. If there is a mediation effect through bidding characteristics between PDS and cost performance, the cost growth should be included to measure the variance between the owner's pre-bid estimate and contract amount.

However, most of the previous research measures the duration only between contract and completion of a project for the cost performance metrics. Figure 6.4 depicts two types of durations. The upper duration in the figure presents the difference between contract and final cost measured by previous research. The other duration shows the project phase influenced by bidding characteristics. Therefore, this research suggests a different approach to measure cost growth.

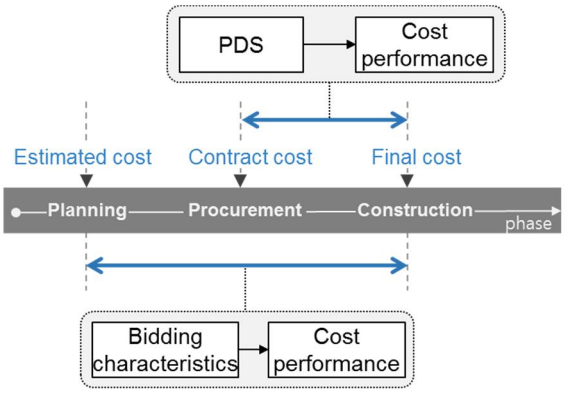



**Figure 6.4** Inconsistent formulation in the measurement of cost growth as a cost performance metric

In addition to the research conducted by Shrestha et al. (2017), this research provides a theoretical basis for the operational definition of cost growth to be divided into three formulations including bidding stage cost variance. Then, when the effect of PDS on cost performance is mediated by bidding characteristics, not only design and construction cost growth (Eq. 2.5) but also contract award cost growth (Eq. 2.4) and total cost growth (Eq. 2.6), should each be measured in order to improve the evaluation of the PDS.

## 6.5 Summary

This chapter discussed the cost performance between DB and DBB delivery systems presenting another dimension of comparison by considering the full life cycle. The comparison was conducted in two ways: comparison by project types, and comparison by bidding characteristics.

For the first comparison, an independent-sampled *t*-test with equal variances was performed to verify whether the mean values of cost growth for DB and DBB building and civil projects were significantly different. Architectural building projects were determined to be statistically significant project types for the mediation analysis, while civil infrastructure projects presented no statistical significance, as discussed in the previous chapter. Although the building projects showed that the mean value difference in cost growth between DB and DBB was statistically significant and DB presented lower cost growth than that for DBB, the superiority of DB in terms of cost-savings is uncertain. The DBB system for building projects revealed that PDS was subject to mediation effects through bidding characteristics. On the other hand, the t-test results for civil projects indicated that that the DB system for civil projects was superior to the DBB system, although the results were not significant statistically. The mediation effects for civil projects of PDS on cost

performance were not significant and the t-test results could be consistent with the results of previous research using descriptive statistics.

For the second comparison by bidding characteristics, the project cost changes were plotted according to time variance (i.e., project phases) to compare DB and DBB based on building projects. To include bidding characteristics in the comparison, the cost changes of a project should be compared associated with project phases right before and after the bidding phase, since the project cost for public building projects is mediated by bidding characteristics. The time-variance plot showed that the total cost growth including the planning, bidding, and construction phase for DB had higher cost growth than that for DBB. The total cost growth was calculated to be the final project cost as compared to the owner's pre-bid estimation. Although DB for building projects showed lower cost growth during the construction phase, the cost savings for DB was controversial in this case.

With the comparison results, this research proposes three practical applications. First, public-sector owners should consider the bidding characteristics that mediate the effect of PDS on cost performance while evaluating or selecting a DBB delivery system for various types of public buildings in the city (e.g., residential, hospital, library, office, or community center). Second, in order to formulate cost growh as a performance metric, one

should consider not only the costs in the construction phase but also the costs in the bidding stage. Lastly, this research proposes a change in categorization from highway to civil project.

# Chapter 7

# Conclusions

This chapter summarizes research results from the proposed approach to analyze the cost performance of PDSs, particularly focusing on the findings and implications. The contributions of this research are also described, focusing on the technical and methodological aspects. The limitations of this research that should be addressed in future research are introduced with feasible goals for applying the results widely in performance analysis of different PDSs.

## 7.1 Research Results

This research developed an approach to analyze the cost performance of DB and DBB delivery systems using causal analysis. In contrast to the findings of previous research, this study presents a case in which the DB system for building projects should not be considered superior to DBB systems despite overall lower cost growth. Most previous research comparing DB and DBB systems have measured cost growth as a cost performance metric, whereas some others have revealed that contractors use cost growth to achieve

profitability based on bidding characteristics (wherein the level of competition affects the bid price). Other research has explained that bidding characteristics affect the relationship between PDS and cost performance.

However, those research does not distinguish between the effects of PDS and bidding characteristics on cost performance to determine the significant factor affecting cost growth. The current research adopted a causal relationship methodology using path analysis to identify the mediating role of bidding characteristics and to quantify both the direct and indirect (i.e., mediation) effects of PDS on cost performance. Public-sector projects in Seoul were investigated to clarify the differences in cost growth for DB and DBB systems with reference to architectural building and civil infrastructure project types. Prior to the mediation analysis, this research also conducted a moderation analysis. A simple moderation model was proposed to examine whether the project type moderates the impact of the PDS's effects on cost performance.

By testing the hypotheses, this research determined the causal factors of cost performance, where DBB systems were used in public-sector building projects. Project type moderates the effects of PDS on cost performance (supporting Hypothesis 1). The bidding characteristics play a mediating role in the relationship between PDS and cost performance (supporting Hypothesis 2). In this research case, the DBB system has a mediation effect on cost

performance. Although the t-test results reveal a significant mean difference between DB and DBB systems, the evaluation of cost savings for the DB system yielded inconsistent results. For civil infrastructure projects, no mediation effect of bidding characteristics on the relationship between PDS and cost performance was found. The traditional t-test method was used to compare mean value differences, and the results revealed no significant difference in cost growth between DB and DBB systems. However, the descriptive statistics indicated that the cost growth in DB systems was lower than that in DBB systems.

## 7.2 Research Contributions

This research thus contributes to the body of knowledge in the field of construction engineering and management as it indicates that PDSs have the potential to be misjudged when their cost-effectiveness is mediated by bidding characteristics. It suggests that lower cost growth should not always be considered a benchmark for better performance. Moreover, to the best of the author's knowledge, this research is the first to employ a causal analysis to evaluate PDS performance by testing this issue hypothetically using an empirical comparison.

The research findings are expected to enhance the evaluation of PDS in terms of cost performance, provide a better understanding of the mechanisms by which PDS impacts cost performance, help project participants to select an appropriate PDS by considering moderating effects on specific project types, and in turn, provide guidance for public-sector owners and A/E who manage building and civil projects. According to the results, the project owner and A/E should not conclude that DB public building projects outperform DBB ones, although the former could result in lower cost growth. Since the sample size of the comparison model, with 82 DB and 115 DBB projects, was sufficiently large and the project types represent a wide variety of public-sector building

and civil projects, the study's results have global applicability in urban public projects.

The academic contribution of this research is to identify the theoretical attributions of project type as a moderator and bidding characteristics as a mediator influencing the causal relationship between PDS and cost performance, and to empirically validate the theory. The practical words in the field of construction management have been mapped to academic terminologies.

## 7.3 Future Research

This research has limitations in that it did not consider value engineering costs for improvement due to data limitations. Also, it is necessary to compare a project's full life cycle costs, including the maintenance cost, to understand a full cost performance of a PDS. The operational definition of the cost performance metric varies depending on the research. Inconsistent cost performance metrics should be unified for better analysis of PDS cost performance. Performance evaluation of a PDS should not only consider cost but also time, quality, safety, etc. However, this research addressed cost performance because the subject is debatable and is assumed to be counterfactual.

It is necessary to improve further the applicability of the methods developed in this research to include the various situations of cost performance due to the PDS. Besides, various combinations of project types should be applied to specify the research scope and enhance the comparison of PDS. The future scope of this research includes adjusting the cost performance metric according to the PDS. Finally, to improve the causal analysis model, future research should identify additional third factors (e.g., conditional moderators, mediators, and confounders) associated with the relationship between the PDS

and cost performance. In turn, the models should be developed as conditional process models (e.g., mediated moderational effects, moderated mediational effects) that can be integrated to examine the mediation and moderation effects in a single model. That is, moderated mediation and mediated moderation models considering project characteristics and bidding characteristics simultaneously need to be applied. Those models are expected to enhance the explanation around inconsistent evaluation results of the cost performance comparison between DB and DBB delivery systems.

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# LIST OF APPENDICES

# Appendix A: Terminology

| Term. | Acronym | Explanation |
|---|---|---|
| Change order | - | A written order to the contractor signed by the owner and architect, issued after execution of the contract, authorizing a change in the work or an adjustment in the contract sum of the contract time (article 12.1.1 of AIA A201). Moreover, the same terms are used in other countries; "variation order" was coined in UK, and FIDIC adopted the term "variation". |
| Construction management at risk | CMR | A project delivery system where the owner contracts separately with a designer and a contractor (Konchar and Sanvido 1998). |
| Cost growth | - | It stands for various terminologies, such as cost changes, overrun/underrun, variance, escalation, deviation, discrepancies between initial and final contract amount. |
| Design-build | DB | A project delivery system where the owner contracts with a single entity to perform both design and construction under a single design-build contract (Konchar and Sanvido 1998). |
| Design-bid-build | DBB | The traditional project delivery system in the U.S. construction industry where the owner contracts separately with a designer and a constructor (Konchar and Sanvido 1998). |
| Endogenous variable | - | The word "endogenous" means "from within," and every endogenous variable has at least one cause, which is usually placed in the left side of a causal relationship model diagram (Kline 2018). |

| Term. | Acronym | Explanation |
|---|---|---|
| Exogenous variable | - | The word "exogenous" means "from without (the outside)," and whatever causes exogenous variables are not represented in a causal relationship model; that is, their causes are unknown as far as the model is concerned (Kline 2018). |
| Mediation effect | - | Mediation is a causal model (Rose et al. 2004; Wengener and Fabrigar 2000) that explains the process of "why" and "how" a cause-and-effect happens (Baron and Kenny 1986; Frazier et al. 2004). Hence, a mediational analysis attempts to "identify the intermediary process that leads from the independent variable to the dependent variable" (Muller et al. 2005, p. 852). In other words, in a simple mediational model, the independent variable is presumed to cause the mediator, and in turn, the mediator causes the dependent variable. For this reason, a mediation effect is also termed an indirect effect, surrogate effect, intermediates effect, or intervening effect (MacKinnon et al. 2002; Wu and Zumbo 2008). |
| Mediator (intervening variable) | - | A mediator is a third variable that links a cause and an effect (Wu and Zumbo 2008). A variable that carry the influence or reflect the mechanisms of the effect of X on Y (Cohen et al. 2003). |
| Moderation effect | - | A moderation effect is a causal model that postulates "when" or "for whom" an independent variable most strongly (or weakly) causes a dependent variable (Baron and Kenny 1986; Frazier et al. 2004; Kraemer et al. 2002; Wu and Zumbo 2008). |

| Term. | Acronym | Explanation |
|---|---|---|
| Moderator | - | A moderator is a third variable that modifies a causal effect. In essence, a moderator modifies the strength or direction (i.e., positive or negative) of a causal relationship (Wu and Zumbo 2008). |
| Path analysis | - | Path analysis is a form of structural equation modeling (SEM), and a technique to analyze the influential relationships not only between independent and dependent variables but also among different independent variables simultaneously (Loehlin 1998; Kline 2011). Path analysis is the oldest member of the SEM family, but it is not obsolete (Kline 2018). |
| Project Delivery System | PDS | PDS is defined as the procurement method which includes the project scope, organizational structure, contract method and award method (Gordon 1994). |
| Project type | - | Type of facilities, this research uses data from public sector, there are two main project types used for mediation effects model: building and civil projects. civil infrastructure projects are divided into sub-project type: tunnel, bridge, highway, water sewage, public building projects are divided into sub-project type: library, community-center, public school, county office, residential building, non-residential building |
| Structural equation modeling | SEM | Structural equation modeling (SEM) is a form of causal modeling that includes a diverse set of mathematical models, computer algorithms, and statistical methods that fit networks of constructs to data (Kaplan 2008; Wikipedia). SEM includes |

| Term. | Acronym | Explanation |
|---|---|---|
| | | confirmatory factor analysis, confirmatory composite analysis, path analysis, partial least squares path modeling, and latent growth modeling (Kline 2011; Wikipedia). Other terms such as covariance structure analysis, covariance structure modeling, or analysis of covariance structures are also used in the literature to classify these techniques under a single label (Kline 2018). |

# Appendix B: Descriptive Statistics of Samples

| Project type | Project delivery system | | N | Mean value | S.D. | S.E. |
|---|---|---|---|---|---|---|
| Residential building | Cost growth | DB | 11 | 12.75 | 7.52 | 2.27 |
| | | DBB | 30 | 13.58 | 8.67 | 1.58 |
| | Bid to estimate ratio | DB | 11 | 93.89 | 6.77 | 2.04 |
| | | DBB | 30 | 77.79 | 7.20 | 1.31 |
| Non-residential building (Public building) | Cost growth | DB | 23 | 5.12 | 6.97 | 1.45 |
| | | DBB | 26 | 15.53 | 13.81 | 2.71 |
| | Bid to estimate ratio | DB | 23 | 93.60 | 5.19 | 1.08 |
| | | DBB | 26 | 81.22 | 5.50 | 1.08 |
| Building | Cost growth | DB | 34 | 7.59 | 7.91 | 1.36 |
| | | DBB | 56 | 14.49 | 11.28 | 1.51 |
| | Bid to estimate ratio | DB | 34 | 93.69 | 5.64 | 0.97 |
| | | DBB | 56 | 79.39 | 6.63 | 0.89 |
| Civil | Cost growth | DB | 48 | 11.71 | 20.28 | 2.93 |
| | | DBB | 59 | 15.40 | 21.33 | 2.78 |
| | Bid to estimate ratio | DB | 48 | 89.17 | 10.98 | 1.58 |
| | | DBB | 59 | 83.38 | 6.82 | 0.89 |

Note: DB = design-build; DBB = design-bid-build; N = sample size; S.D. = standard deviation; S.E. = standard error

# 국 문 초 록

## 조절효과 및 매개효과를 이용한 설계·시공 일괄입찰과 분리입찰 발주방식의 비용성과 비교

본 연구는 설계·시공일괄입찰(DB, design-build)과 설계·시공 분리입찰(DBB, design-bid-build) 발주방식의 성과를 비용측면에서 분석하여, 측정지표인 건설프로젝트 비용증가율이 낮게 나타나는 발주방식을 항상 우수하다고 할 수 있는지 여부를 조사합니다. 기존 연구들은 발주방식 별 비용성과를 비교할 때, 이들 사이에 제 3 의 영향인자(예: 프로젝트 유형, 입찰특성)가 존재함을 인식하였으나, 그 영향관계를 규명하지 못했습니다. 따라서, DB 와 DBB 발주방식을 비교할 때 발주방식과 제 3 의 영향인자 중 어느 요인이 비용성과에 유의미한 영향을 미치는지 확인할 수 없었고, 성과분석 결과가 불일치하게 도출되었지만 원인을 규명하지 못했습니다. 이에, 본 연구는 발주방식의 비용성과에 제 3 의 요인이 언제, 어떻게 영향을 미치는지 규명하여 성과분석을 향상시키고자 인과관계 분석기법을 제안하였습니다. 먼저, 문헌분석을 통해 기존연구를 세 가지 범주로 구분하였습니다: (1) DB 와 DBB 발주방식의 성과비교 연구, (2) 프로젝트 비용성과에 영향을 미치는 요인분석 연구, (3) 발주방식과 비용성과의 관계에서 발주방식과 제 3 요인과의 연관분석 연구. 본 연구에서는 이러한 3 가지 범주를 하나의 인과관계 모델로 통합하여, 프로젝트 유형에 의한 조절효과(Hypothesis 1)와 입찰특성에 의한 매개효과(Hypothesis 2)를 설정하는 연구가설을 수립하였습니다.

대한민국 서울시에서 발주한 공공부문 프로젝트를 기반으로 연구를 수행하였고, 프로젝트 유형에 따라 발주방식의 비용성과가 영향을 받는다는 조절효과 분석은 매개효과 분석 이전에 수행되어, DB 와 DBB 의 비용 성과를 비교할 때 프로젝트 유형을 제어해야 하는지 여부를 결정했습니다. 또한, 발주자와 계약자 간 프로젝트 비용증가에 대한 서로 다른 관점을 동시에 반영, 발주방식에 의해 입찰특성과 프로젝트 비용이 영향을 받는다는 메커니즘을 매개효과 분석모델을 통해 규명하였습니다. 이 모델은 경로분석을 이용하여 발주방식과 입찰특성이 비용성과에 미치는 영향들을 분류하고 어느 영향이 비용증감에 통계적으로 유의미한지 결정하는 역할을 합니다.

최종적으로, 두 연구가설이 검증된 결과를 바탕으로 프로젝트 유형 및 입찰특성에 따른 DB 와 DBB 비용성과를 비교하였습니다. 건축분야 프로젝트에서 DBB 방식의 비용증감은 입찰특성에 의해 매개되지만, 토목분야 프로젝트에는 매개효과가 존재하지 않는 것으로 나타났기 때문에, 이는 기존 연구방식에 의한 평균차이 검증결과 비용증가가 낮음에도 불구하고 DB 가 DBB 보다 우월한 것으로 간주되어서는 안 되는 조건을 나타냅니다. 따라서, 발주방식별 비용에 대한 효율성이 입찰특성에 의해 매개될 때 잘못 평가될 가능성이 통계적으로 검증되었습니다. 본 연구는 조절효과 및 매개효과를 기반으로 DB 와 DBB 발주방식의 성과분석을 향상시키는 연구모델을 제안함으로써 건설관리분야 지식체계에 기여합니다. 또한, 실무자(예: 공공부문 발주자 및 설계·엔지니어)가 특정 프로젝트 유형에 대해 발주방식을 평가하거나 선정할 때 참고할 수 있는 지침을 제안합니다.

**주요어:** 발주방식(Project Delivery System); 설계·시공일괄입찰(DB); 설계·시공분리입찰(DBB); 비용성과; 인과관계분석; 매개효과; 조절효과; 경로분석

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