THE IMPACTS OF BIM IMPLEMENTATION ON CONSTRUCTION PROJECT PRODUCTIVITY: EXPERIENCES FROM CHINA

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2017

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A thesis submitted in partial fulfilment of the requirements for the degree of Master of Philosophy

January 2017

CERTIFICATE OF ORIGINALITY

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ZHOU Xin

Abstract

Construction productivity has long been a concern in both industry and academia, for it can be improved to foster sustaining economic growth and generate substantial social wealth and welfare. Being the most dominating factor contributing to the remarkable economic profitability of most construction projects, productivity is receiving incessantly increasing concern with respect to the production efficiency of the whole construction industry. However, construction industry worldwide has been undergoing a substantial and continuous decrease in construction productivity over the past several decades. During the past ten years, the construction productivity growth rate of China has decreased dramatically combined with the decline of the average growth rate of labor productivity of China.

Driving by the increasing pressure of improving productivity, over the recent several decades, the architecture, engineering, and construction (AEC) industry has long been making every effort to seek effective approaches to reduce cost, shorten project duration, enhance the quality of construction projects thus to improve productivity. BIM was most commonly perceived as a visualization tool for coordinating and promoting communication of AEC sector in order to reduce rework, predict collisions, enhance project productivity, shorten project time, decrease project costs, and improve quality and safety of construction projects. Generally, BIM is regarded as an emerging, promising, and innovative technology and process, dramatically transformed the way of a building from the original conception onwards to demolition. It allows multiple disciplinary information to be encapsulated within one model, and dramatically transform the conventional design formats and communication approaches of AEC sector whereby players depend heavily on 2D CAD-based model towards a 3D digital interacted model. However, research on showing a clear

understanding of the impacts of BIM on construction productivity through BIM implementation is scarce.

A comprehensive review of existing research in BIM implementation and construction productivity reveals the research gaps. First, as BIM has been evidenced by many researchers as an effective means for facilitating design processes, reducing design error, thus to achieve productivity gains, numerous previous researchers have investigated the attributable factors affecting design error, attempting to seek out effective strategies to prevent or mitigate design errors. However, rare empirical research has been placed on quantifying the impacts of BIM on design error reduction, and quantitatively measuring the extent to which attributable factors could have the better ability to contain design error. In addition, due to the great potential of BIM for addressing construction inefficiencies and lower productivity in the construction projects, the past decade has witnessed an increasing research interest in BIM both in design and construction stage. Nevertheless, the large majority of prior studies have primarily concentrated on identifying incentive factors and barriers of BIM adoption in the construction industry, or on reporting the business value or potential profitability of applying BIM. Sparse scholarly attention has been focused on quantitatively demonstrating the principal impacts of BIM implementation on construction productivity at project level during the construction stage.

To fill this research gap, this research aims to identify the impacts of BIM implementation on construction productivity. The following objectives are achieved in this research: (1) to conduct a comprehensive review of the extant research theories related to the status of BIM implementation and basic characteristics of construction productivity; (2) to theoretically develop a BIM-enabled design error reduction (DER) model during design stage, as well as build up a conceptual framework regarding BIM-based construction productivity gains model; (3) to examine the impacts of BIM implementation in reducing design error by using the conceptual model based on the different design error reduction (DER) indicators; (4) to test the conceptual model for probing deeper into how and to what extent the implementation of BIM can influence the project-level construction productivity based on the empirical data from BIM-based construction projects.

Through document analysis, research gaps, as well as the related definition of construction productivity and BIM, were identified in achieving objective 1. By a subsequently further literature review, a design error reduction model and BIM-enabled construction productivity gains model have been developed. Questionnaire survey and semi-structured interview were used to collect project-based data in order to test the proposed model. Descriptive statistics and multiple regression analysis were utilized to investigate and analyze the data for achieving objectives 3 and 4.

The primary findings obtained in this study include the following aspects. First, research gaps on quantifying the impacts of BIM implementation on construction productivity has been identified through a comprehensive literature review. Then, a conceptual framework of design error reduction model is developed to evaluate the impacts of BIM implementation in reducing design error during the design stage. Furthermore, BIM-enabled construction productivity gains model has also been built up to assess the impacts of BIM implementation on construction productivity during the construction stage. After the development of these models, empirical data is utilized to test the proposed models. For the DER model, six attributable factor (including clash detection, design system coordination, drawing error, teamwork and cooperation, constructability, and practicality, and knowledge and information management) are found to be positively statistically associated with the aggregate impacts of BIM implementation on design error reduction, among which clash detection has the best ability to positively affect design error reduction. For the BIM-enabled construction productivity gains model, reflective constructs (incorporating labor productivity, communication and coordination, site resource planning and management, simulate master schedule and construction sequences, shorten project duration, quantity takeoff and cost estimation, and minimize project cost) are all positively statistically significant with productivity performance ratio, suggesting that productivity performance ratio increases with these seven reflective factors.

This research can enrich theoretical development in the fields of BIM and construction productivity by reviewing the existing research. The research findings and gaps identified in previous studies could serve as the basis for recommending future research in relevant fields. As an exploratory effort to build up the relationship between BIM and construction productivity, a design error reduction model and BIM-enabled construction productivity gains model have been developed to identify the potential relationship between BIM implementation and construction productivity both in design and construction stage. This model could also be used by researchers for future investigation. Furthermore, the findings derived from this research could help to develop a more comprehensive understanding of the reasons why construction organizations implement BIM in construction projects and provide a more dynamic picture of how construction productivity may vary as the attributable factors change.

Acknowledgements

First, I want to thank my chief supervisor, Dr. Johnny K.W. Wong. Being his MPhil student is a great honor. He taught me what a good research is. I appreciate his contributions of time, ideas, and funding to make my MPhil experience productive and stimulating. His rigorousness and enthusiasm for research were contagious and motivating, even during the tough times of my pursuit for my MPhil. I am also thankful for the excellent example he provided as a successful scholar. My sincere gratitude is also dedicated to my co-supervisor, Prof. Albert P.C. Chan, for his generous guidance and support, particularly on the provision of research directions during my study.

Special thanks also go to Mr. Jason Low for his kind support during the period of my MPhil study. I would like to thank Dr. Chao Mao for her kind assistance and support in my research. My deep appreciation also goes to Yang Du and Jiaojing Ren, who provide me resources for data collection. I am grateful to the administrative staff of the BRE Department, particularly Ms. Chloe Shing and Ms. Gracie Ip for their thorough guidance, infinite patience, and kind suggestions.

Last but not least, I would like to thank my family and friends for their continuous understanding, support, and encouragement.

Table of Contents

List of Figures

List of Tables

CHAPTER 1 INTRODUCTION

1.1 Introduction

This chapter introduces the research background, identifies the research gaps, and proposes the research aims and objectives. Then, the significance and value of the current study are highlighted. Finally, the structure of the thesis is presented.

1.2 Research Background

China's construction industry has been playing a progressively leading role in the process of national economic growth (Lu and Fox, 2001). According to China Statistical Yearbook (2014), construction industry achieved 3.9 trillion Yuan in terms of total output value in 2013, accounting for 6.90% of the national gross domestic product (GDP) of China. During the last several decades, Chinese construction industry experienced a fluctuant variation in the share of GDP, but it has maintained a sustained increase over the last ten years (Figure 1.1). Due to the unceasingly growing proportions in the share of GDP together with the commencement of Open Door Policy (Chen, 1998), China's construction industry has faced the severe challenge and incremental competitiveness from worldwide. This situation was further reinforced by the accession of China into the World Trade Organization (WTO) due to the market globalization. Therefore, it is indispensable to develop an effective and efficient approach to improve competitiveness and performance of Chinese construction industry so as to sustain China's economic development (Xue et al., 2008).

Construction productivity has long been a concern in both industry and academia, for it can be improved to foster sustaining economic growth and generate substantial social wealth and welfare (Park et al., 2005; Kenley, 2014; Tookey, 2011). Driving by the increasing pressure of improving productivity, over the recent several decades, the architecture, engineering, and construction (AEC) industry has long been making every effort to seek effective approaches to reduce cost, shorten project time, enhance the quality of construction projects thus to improve productivity (Azhar, 2011). Being the most dominating factor contributing to the remarkable economic profitability of most construction projects (Yi and Chan, 2014; Kenley, 2014), productivity is receiving incessantly increasing concern with regard to the production efficiency of the whole construction industry. Although economic growth is not only decided by the productivity, it is a significantly crucial determinant measuring the performance of the whole construction industry of China.

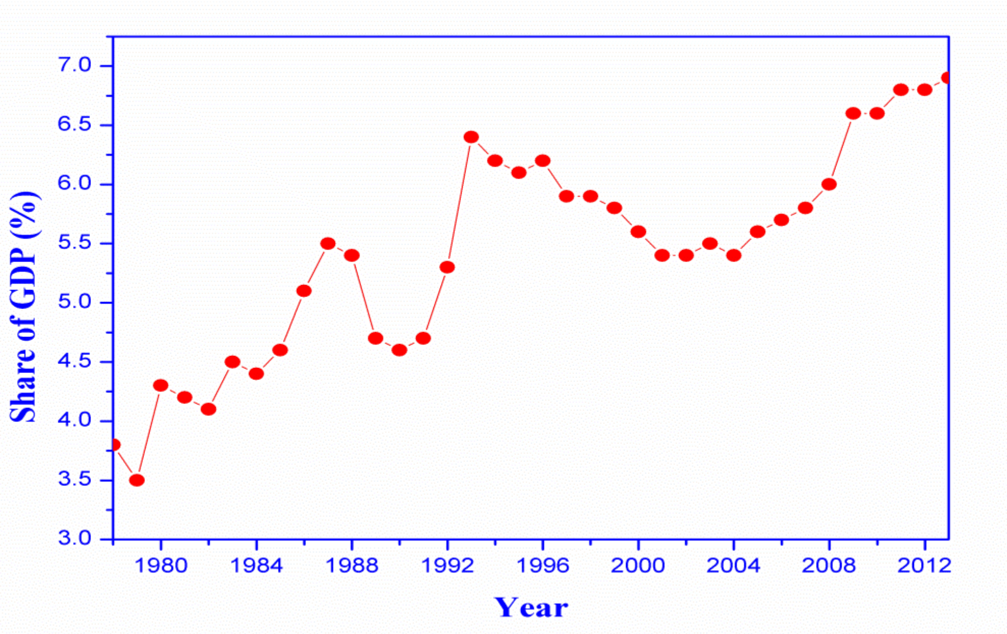


Figure 1.1 Construction Industry's Share in GDP of China, 1978-2013

(Source: China Statistical Yearbook 2014)

However, serving as the most predominant and challenging industry of the world, construction industry has been undergoing substantial and continuous decrease in construction productivity over the past several decades (Arditi, 1985; Tucker, 1986; Rojas and Aramvareekul, 2003b; Rojas and Aramvareekul, 2003a; Crawford and Vogl, 2006; Siriwardana and Ruwanpura, 2012; Bröchner and Olofsson, 2012). According to

China Statistical Yearbook (2012), the productivity growth rate of China has decreased dramatically since 2007 (Figure 1.2). Besides, the average growth rate of labor productivity of China has fallen since 2004 (Figure 1.3). It declined from 0.2 in 2004, through a turbulent period, eventually down to 0.09 in 2011. Consequently, China's construction industry has the urgency to improve productivity. In order to investigate related factors leading to the decline in productivity, factors affecting construction productivity have been explored by a number of scholars, for it is a prerequisite for improving productivity (Mojahed and Aghazadeh, 2008). These contributory factors include labor productivity, planning and scheduling, rework (quality control), change orders, cost, technology, communication, and so forth. Thus, the construction industry has been facing a large paradigm shift to improve productivity and reduce overall costs of construction projects through effective coordination, cooperation, and communication of all stakeholders and practitioners (Arayici et al., 2012).

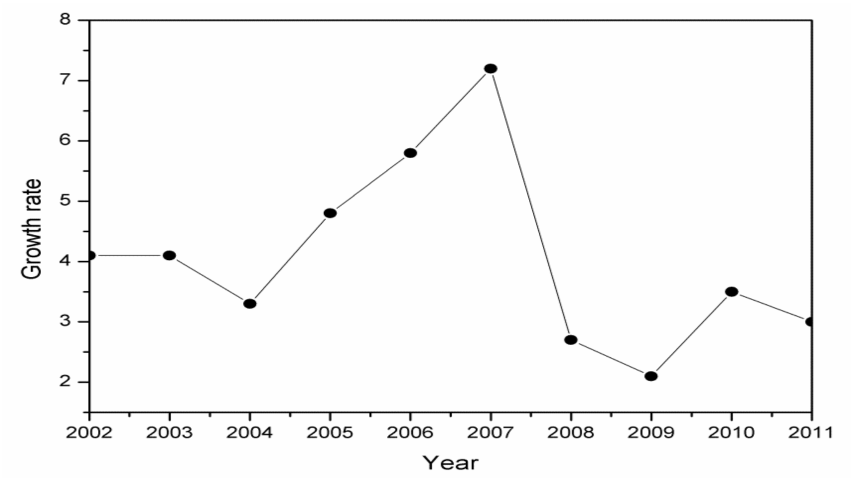


Figure 1.2 Construction Productivity Growth Rate of China, 2002-2011

(Source: China Statistical Yearbook 2012)

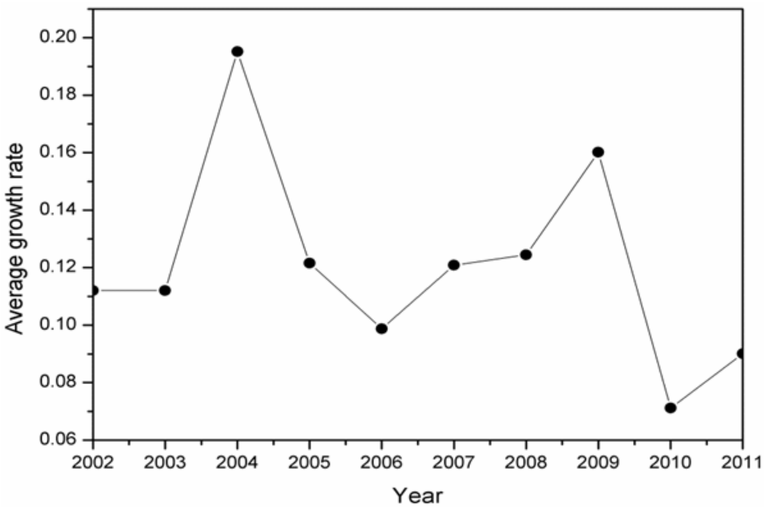


Figure 1.3 Average Growth Rate of Construction Labor Productivity, 2002-2011

(Source: China Statistical Yearbook 2012)

Many of efforts have been made to improve construction productivity, such as design-building project delivery system (Dahl et al., 2005), lean construction (Sacks et al., 2010a), construction virtual prototyping (CVP) technology (Huang et al., 2007), augmented reality (AR) (Wang et al., 2014b). In recent years, the architecture, engineering, and construction industry have witnessed an expanding adoption of building information modeling (BIM) in construction. As stated by Brynjolfsson and Yang (1996), the contribution of a new technology can be properly measured by productivity efficiently and effectively. Besides, productivity improvements are noticeable through the utilization of transformative new information technology by improving communication among all stakeholders (Triplett and Bosworth, 2004). Wei and Lin (2004) also ascertained that much attention should be placed on the development of information technology due to its innovative and integrated features. As construction industry are being confronted with great challenges to improve productivity, efficiency, and profitability of construction projects (Arayici et al., 2011b), BIM is currently considered as a transformative information technology to achieve these goals.

BIM is regarded as an emerging, promising, and innovative technology and process, dramatically transformed the way of a building from the original conception onwards to demolition (Hardin, 2011; Azhar et al., 2012). Succar (2009) defines BIM as a visualization tool or an integrated process that generates a systematic approach to simulate and manage the design, construction, and operation information of a building in digital model throughout its lifecycle. As BIM allows multiple disciplinary information to be encapsulated within one model, it serves as a dynamic repository providing synchronous physical and functional information of a building varying from design, construction, operation, maintenance, till to demolition (Lu and Li, 2011). BIM also gives rise to all the practitioners incorporated in the construction projects, like government, owners, designers, contractors, construction professionals, supervisors, and so on, to utilize and manipulate information in the models (Li et al., 2014a). BIM thus dramatically transform the conventional design formats and communication approaches of AEC sector whereby players depend heavily on 2D CAD-based model towards a 3D digital interacted model.

As the increasing challenges faced by China's construction industry due to the market globalization after the commencement of reform and opening policy and the accession to the World Trade Organization (WTO), it is indispensable to develop an effective and insightful approach to improve the whole productivity and competitiveness of China's construction industry (Xue et al., 2008). With the ever-escalating pressure of improving construction productivity, BIM was most commonly perceived as a visualization tool for coordinating and promoting communication of AEC sector in order to reduce rework, predict collisions, and enhance productivity, time, cost, quality and safety of a construction project (Zuppa et al., 2009). However, the relationship between BIM and construction productivity has not been empirically and distinctly identified and measured due to lack of quantitative measurements for evaluating the impacts and value produced by the application of BIM. In addition, grounded on the inconclusive and uncertain outcomes both in monetary and managerial aspects, construction professionals are confronted with the dilemma of making a decision whether to recognize and enforce BIM technology in construction projects (Succar, 2010; Barlish and Sullivan, 2012; Li et al., 2014a).

Recently, a number of studies have been focused on facilitating the implementation of BIM in Mainland China. Zhang et al. (2011) proposed a 4D-BIM dynamic approach to monitoring construction resource and cost in real-time in order to enhance the level of management and cost control. Li et al. (2010) suggested that the developer-driven approach was frequently recognized as the most efficient way to promote the application of BIM technology in China. He et al. (2012) pointed out that, while the development of BIM technology in China was still in preliminary stage, it would be broadly applied to the whole construction industry of China. Also, the main barriers of broadly implementing BIM in China have been investigated and analyzed by Zhang (2010). Results indicated that values and benefits of BIM usage can be really realized at some stage, but the lack of professional knowledge regarding BIM and inefficiency of current construction system are the major factors inhibiting the development of BIM implementation in China. However, research on showing a clear understanding of the impacts of BIM on construction productivity and quantify the productivity gains through BIM implementation is scarce. Thus, based on the current status of BIM implementation in China, there is a great need to find out a way to obtain significant productivity improvements by implementing BIM technology. This study attempts to fill this knowledge gap by examining the current BIM practices, identifying contributory factors of productivity, develop a preliminary conceptual framework regarding BIM and productivity relationship. In addition, this study will leverage the relationship of BIM implementation on each of productivity gains indicators so as to measure the extent to which these indicators have the better ability to improve construction productivity with the implementation of BIM.

1.3 Research Gaps

Due to the great potential of BIM for addressing construction inefficiencies and lower productivity in the construction industry, the past decade has witnessed an increasing research interest in BIM both in design and construction stage. As illustrated in Chapter 2, the large majority of prior studies have primarily concentrated on identifying incentive factors and barriers of BIM adoption in the construction industry (Bernstein and Pittman, 2004; Cerovsek, 2011a; Ku and Taiebat, 2011; Gu and London, 2010), or on unfolding project benefits gained from BIM utilization in construction projects (Bryde et al., 2013; Poirier et al., 2015; Hergunsel, 2011; Barlish and Sullivan, 2012), or on reporting the business value or potential profitability of applying BIM (Bernstein, 2015; Bernstein et al., 2012; Young et al., 2009; Lee et al., 2012). Nevertheless, despite of some research having measuring the impacts of BIM on labor productivity at activity level (Poirier et al., 2015; Kim et al., 2015), sparse scholarly attention has been focused on quantitatively demonstrating the principal impacts of BIM implementation on construction productivity at project level during the construction stage.

As illustrated in Chapter 3, BIM has been evidenced by many researchers as an effective means for facilitating design processes (Eastman et al., 2008; Son et al., 2015; Sacks et al., 2010b; Sacks et al., 2010a; Taylor and Bernstein, 2009), reducing design error (Linderoth et al., 2014; Love et al., 2011c; Rajendran et al., 2013), thus to achieve productivity gains (Sacks and Barak, 2008). Additionally, numerous previous researchers have investigated the attributable factors affecting design error (Josephson and Hammarlund, 1999; Love et al., 2012; Love et al., 2011c; Lopez et al., 2010), attempting to seek out effective strategies to prevent or mitigate design errors (Love et al., 2008; Busby, 2001; Love et al., 2012). However, rare empirical research has been placed on quantifying the impacts of BIM on design error reduction, and quantitatively measuring the extent to which attributable factors could have the better ability to contain design error.

1.4 Research Objectives

This research aims to identify the impacts of BIM implementation on construction project productivity based on the questionnaire survey from informed senior and specialized personnel directly participating in BIM-based projects. The specific objectives of this research are shown below:

(1) *To conduct a comprehensive review of the extant research theories related to the status of BIM implementation and basic characteristics of construction productivity;*

(2) *To theoretically develop a BIM-enabled design error reduction (DER) model during design stage, as well as build up a conceptual framework regarding BIM-based construction productivity gains model;*

(3) *To examine the impacts of BIM implementation in reducing design error by using the conceptual model based on the different design error reduction (DER) indicators*

(4) *To test the conceptual model for probing deeper into how and to what extent the implementation of BIM can influence the project-level construction productivity based on the empirical data from BIM-based construction projects*

1.5 Significance and Value of Research

Productivity is of utmost importance to the construction industry as the construction projects become increasingly fragmental to manage and control in China. In the meantime, the rapid development of China's urban construction projects brought about increased urgencies to reduce design and construction duration, and to tighten project budgets and amidst more complex projects. BIM as a fundamentally innovative way of producing, sharing and exerting project lifecycle information, can be applied in all stages of a construction project to support increased productivity gains. Furthermore, BIM is also perceived as a solution to a number of inefficiencies in the construction industry. From an academic perspective, this research can get an overall understanding of factors affecting construction productivity and the impacts of BIM implementation on construction productivity both in design and construction stage. Also, it may lay the foundation of methods for improving construction productivity by the usage of BIM, and quantitatively measure the impacts of BIM implementation on construction project-based productivity in Mainland China. From a practical perspective, this study can show the impacts of BIM on construction productivity and quantify the productivity gains through BIM implementation. Beneficial results of BIM implementation can be a stimulating factor facilitating the application of BIM in Chinese construction projects.

1.6 Structure of the Thesis

The dissertation is organized into seven chapters.

Chapter 1 introduces the whole research picture, including the research background, research gaps to be addressed, overall research aim and specific objectives, and the significance and values of the research. Chapter 2 comprehensively reviews the existing literature from a broad perspective focusing on BIM implementation and construction productivity to lay the foundation of present study. Chapter 3 introduces the research design of the present study, and introduce the research methods and analysis techniques employed in this research. Chapter 4 theoretically develops a BIM-enabled design error reduction model and BIM-based construction productivity gains model. Chapter 5 empirically identifies the impacts of BIM implementation in reducing design error by using the conceptual model based on the different design error reduction (DER) indicators during the design stage. Chapter 6 tests the BIM-based productivity gains model for probing deeper into how and to what extent the implementation of BIM can influence the project-level construction productivity based on the empirical data from BIM-based construction projects.

1.7 Chapter Summary

This chapter outlines the overall picture of this research. Background information is introduced first. The research gaps, and research aim and objectives are proposed and explained. Then, the significance of the research is presented. The structure of the thesis is finally outlined.

CHAPTER 2 AN OVERVIEW OF BIM AND CONSTRUCTION PRODUCTIVITY

2.1 Introduction

With the aim of reviewing the literature so as to laying the foundation of the present study, this chapter begins with comprehensively defining BIM from various perspectives. Section 2.2.2 gives an overview of BIM-related research. Research on current adoption of BIM in the construction industry, general benefits of BIM implementation, limitations of BIM implementation, and interoperability issues are identified from literature review, and some of the leading research paper and surveys are discussed here. Section 2.3 reviews construction productivity. In this section, the definition of construction productivity is verified from different perspectives. Then, productivity measurements are reviewed and categorized based on activity, project, and industry level. Finally, factors affecting construction productivity are further examined and identified. Section 2.4 summarizes this chapter.

2.2 Building Information Modeling (BIM)

2.2.1 Definition of BIM

BIM as a rapid diffusion term, while emerging, aroused a great deal of attention in both construction industry and academia. The ambiguous feature of this term determines the widespread definition from various professions or institutions. In this section, numerous previous studies have been focused on the definition of BIM in different perspectives, and a generally accepted definition will be discussed.

Synonymous terms, such as object-oriented modeling, building product model, construction virtual design, virtual prototyping and nD modeling had been employed to define BIM (Aranda-Mena et al., 2009). The concept of BIM can be originally traced back to the term "integrated project database" (IPDB) proposed by Amor and Faraj (2001). Björk and Penttilä (1989) defines IPDB as "a building product model that contains conceptual structures specifying what kind of information is used to describe the building and how such information is structured." Gann et al. (1996) define it as "a single project database as an electronic data model to which all participants refer throughout the process of design, construction, operation, and maintenance." As an evolution of these terms, the term BIM was initially popularized by Jerry Laiserin in around 2002, referring as a tool of using, transferring and exchanging information (Eastman et al., 2008; Aranda-Mena et al., 2009). With the widespread distribution of the concept both in the construction industry and academia, an abundance of researchers and institutions attempted to define BIM in diverse approaches.

Define BIM as a technology

As indicated by Singh et al. (2011), BIM is "an advanced approach to object-oriented CAD, which extends the capability of traditional CAD approach by defining and applying intelligent relationships between the elements in the building model, including both geometric and non-geometric data such as object attributes and specifications". Eastman et al. (2008) define BIM as "a modeling technology and associated set of processes to produce, communicate, and analyze building models." More specifically, information such as geometric and geographic information, spatial distribution, quantities and attributes of building components, scheduled duration and cost estimation are all embraced and integrated into a BIM model.

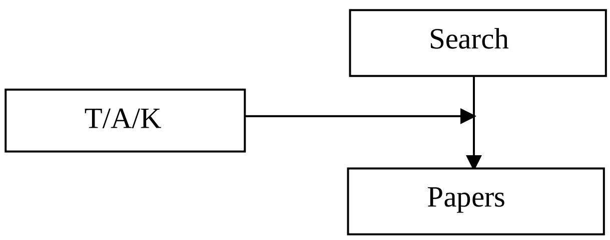
Define BIM as a process

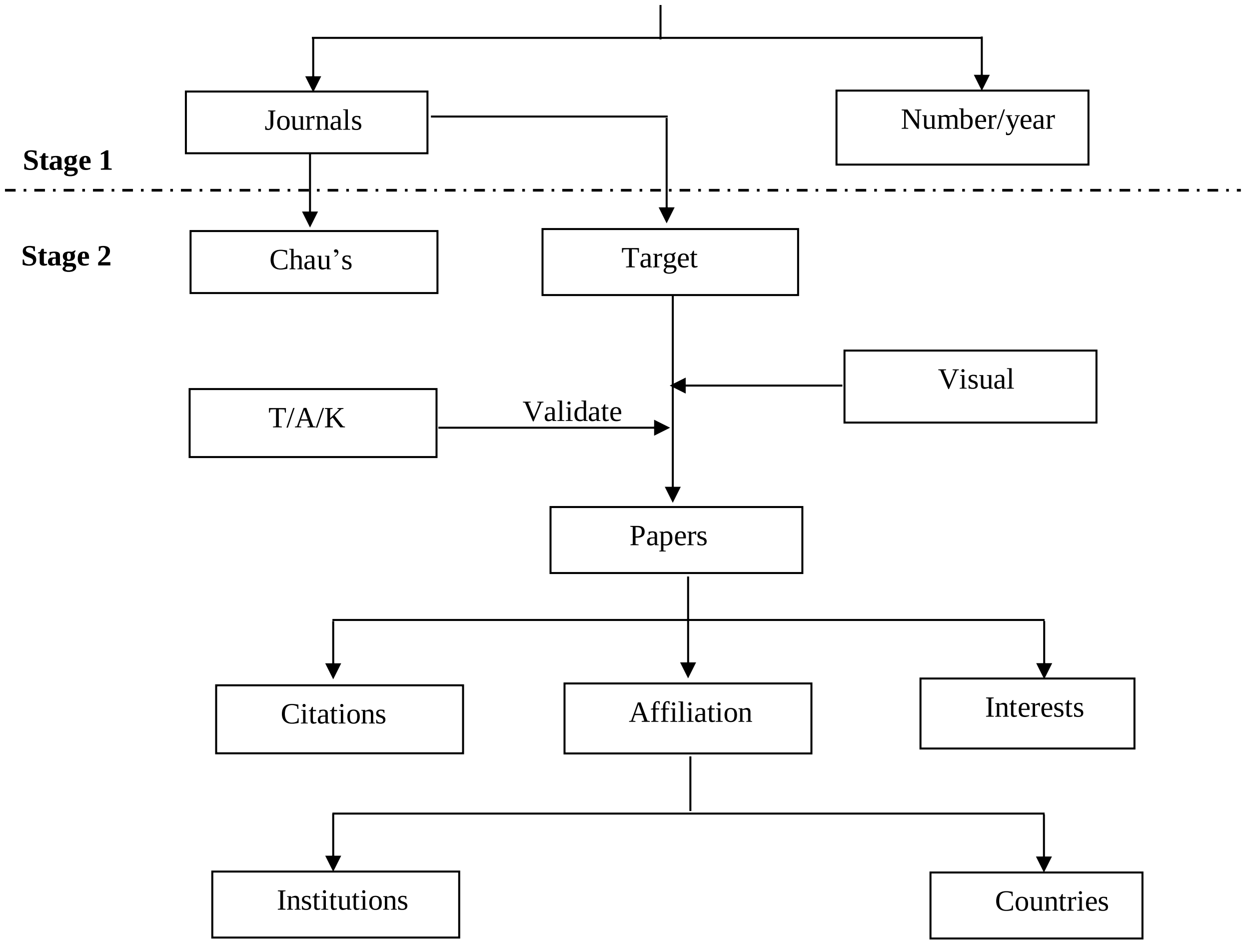
As perceived by Kymmell (2008), BIM is a 3D simulation model of the building and its associated components, developed in the process of planning, design, construction and operation of a building. The Associated General Contractors of America (AGC) maintains that BIM is a data-rich, object-oriented, 3D intelligent and parametric digital representation of a facility, which is created and developed by the usage of the computer-generated model to simulate the process of a facility being conceived, constructed, and operated (AGC, 2005; AGC, 2006). The National Building Information Modeling Standards (NBIMS) committee of USA defines BIM as a shared 3D digital model that carries entire information relating to a facility, including its physical and functional characteristics, and establishing a credible base for decisions during its lifecycle. It is a shared repository of building information data allowing different stakeholders to add, extract or alter information at different stages throughout its lifecycle (NBIMS, 2010). Azhar et al. (2012) define BIM as a virtual process allowing all practitioners to perform and collaborate in one integrated virtual model. The McGraw-Hill (2009) report also defines BIM as the process of creating and using digital models for design, construction and/or operations of projects.

Despite a concerted effort to BIM definitions, no unified consensus is reached to define BIM precisely and accurately. This research followed a generally accepted definition by Eastman et al. (2011), regarding BIM as a modeling approach with its associated building components and a set of processes to generate, coordinate, and analyze building models. This definition was further reinforced by Lu and Li (2011), stating that as BIM allows multiple disciplinary information to be encapsulated within one model, it serves as a dynamic repository providing synchronous physical and functional information of a building varying from design, construction, operation, maintenance, till to demolition.

2.2.2 Overview of BIM-Related Research

Over the past decade, a substantial amount of BIM-related publications has been generated. Retrieval from previous academic journals can provide great benefits from identifying the major research topics, and gaining insightful thoughts into extant research regarding BIM in the AEC industry (Becerik-Gerber and Kensek, 2009), thus to lay the foundation of present study where most efforts are needed and subsequent future research agenda (Wong and Zhou, 2015). The two-stage review methods employed by Tsai and Wen (2005) and Ke et al. (2009) were first adopted to illustrate the major research outputs published in the first-tier journals in terms of a chosen topic. Based on the assumption that a research team may deliver its research outcomes to a high-tier journal with similar topics in its area (Ke et al., 2009), this study first selected a powerful search engine to determine journals that published the most BIM-related articles. The search was further refined by referring to the journal ranking list of Chau (1997) in the fields of construction engineering and management. A three-stage review method was further developed by Hong et al. (2011) to acquire a more elaborated understanding of related research fields. This method aims to improve the coverage of publications which the search engine may miss out, due to the limitation of publication year. Since this study was designed to conduct a documentary analysis of BIM-related papers published between 2006 and 2016, acquiring a distinct and exhaustive investigation of BIM-related research, the two-stage literature review method was deployed, which is depicted in Fig. 2.1.





Note: T/A/K – Title/Abstract/Keywords

Figure 2.1 Review framework (adapted from Ke et al. 2009)

In the first stage, a comprehensive desktop search was conducted based on the "title/abstract/keyword" search method through the powerful search engine *Scopus.* The advanced search Scopus was chosen as it covers a more expanded spectrum of journals, faster citation analysis, and more articles than any other search engine (Falagas et al., 2008). Search keywords contained *building information model(l)ing*, *building information model*, *construction virtual design*, and *construction virtual prototyping*. Papers that included these particular terms in view of the title, abstract, or keywords were possibly considered to meet the requirements of this research. This search was further confined to the subject area such as "engineering," "business, management, and accounting," "social science," "environmental science," "decision sciences," "multidisciplinary," "economics, econometrics, and finance," and "energy" with the document type of "article or review."

The search results derived from stage 1 indicated that a total of 1184 BIM-related papers had been published from 2006 to 2016. To restrict the deviations of unwanted or irrelevant publications, these search results were only analyzed based on the top-ranked construction-related journals and the number of BIM-related articles published annually. Therefore, *Automation in Construction* (AIC) that have published the most BIM-related papers was selected as target journals in stage 2. As the major research of this study is to examine extant research on BIM, academic journals that have high quality and significant impact on the research community of construction were also incorporated in the second stage. Six leading construction journals identified by Chau (1997) were included in the second stage for further analysis: Construction Management and Economics (CME), Engineering, Construction and Architectural Management (ECAM), Journal of Management in Engineering (JME), International Journal of Project Management (IJPM), and Building Research and Information (BRI). Apart from these, Journal of Computing in Civil Engineering (JCCE), another peer-reviewed journal that had published frequently cited BIM-related papers was also added to the final target journal list. Therefore, eight journals were selected for further analysis in total during the second stage. Furthermore, Scopus can cover all of the publications within selected journals from 2006 to 2016.

In the second stage, a more detailed and comprehensive search within the eight target journals was carried out with the help of the same search engine, Scopus. Similar to the first stage, the search at this stage was also confined to the above subject area under the document type of "article or review." Articles under the broad categories of editorial, book review, discussions/closures, and letter to the editor were excluded from the analysis. This resulted in a total of 311 probable BIM-related articles. After the removal of those articles including BIM-related items in the title, abstract or keyword but focused on irrelevant topics, as a result, a total of 305 BIM-related papers were identified. The analyses and review process are primarily based on these 305 identified research papers.

The distribution of the 305 identified papers issued in the eight target journals was shown in Table 2.1 within the period from 2006 to 2016. It is obvious that research on BIM-related studies has been increasing constantly within the studied period. Academic papers issued during the period from 2009 to 2012 had been experiencing a relative stabilized growing trend. Subsequently, the number of published papers dramatically emerged from 2013 to 2016, with a total number of 230 publications indicating a new peak in 2016. Within the studied period, AIC, the most frequently cited journal, was considerably greater than any other target journals, with a total of 183 papers, accounting for 59.67% of all identified papers, followed by 42 papers issued in JCCE, and 36 papers issued in JCEM. The percentage of the three selected journals possess about 85.25% of all 305 papers, indicating the mainstream sources of BIM-related publications within the studied period.

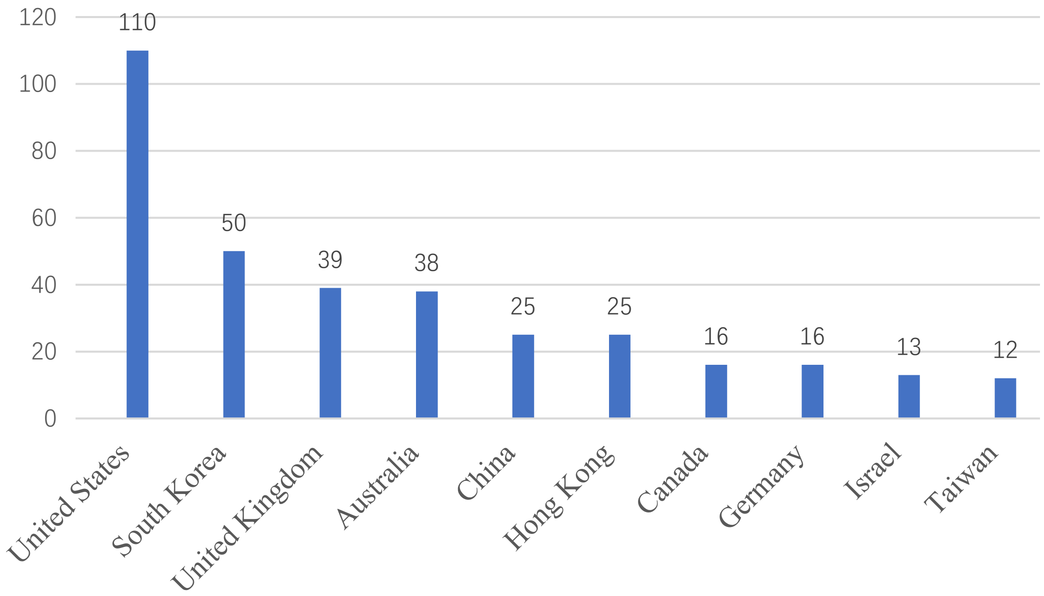
Table 2.1 BIM-related papers issued between 2006 and 2016

Journal list	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total	Percentage
AIC	3	3	2	4	12	14	8	29	37	43	27	**182**	59.67%
JCCE				4	2	1	4	4	3	7	17	**42**	13.77%
JCEM			1	1	2	1	4	7	7	2	11	**36**	11.80%
JME				1			1		8	2	5	**17**	5.57%
CME		1						2	2	3	3	**11**	3.61%
ECAM				1		1	1	1		4	3	**11**	3.61%

IJPM						1		1		1	1	**4**	1.31%
BRI				1			1					**2**	0.66%
Eight journals	3	4	3	12	16	18	19	44	57	62	67	**305**	100.00%

Research papers and reports can be a representative symbol implying the extent to which industrial research and development (R&D) of a specific area was developed. The number of academic research publications in a country may indicate the development level of the industrial innovation and practices in this research area of the particular location. As shown in Fig. 2.2, the country of origin published the most BIM-related papers was U.S., with a total of 110 identified papers, follow by 50 papers in South Korea, 39 papers in U.K. and 38 papers in Australia. The total amount of BIM-related papers published with the first authorship in the four countries comprised 77.7% (237 out of 305) of the total identified papers in the target journal. The contribution of these four countries to BIM-related research was considerably higher than that of other countries or regions. These facts may be perceived as logical and understandable when examining the degree of implementing BIM in construction projects within the four developed countries. Construction industrial practices with great emphasis on information technology such as BIM greatly boosted the development of BIM-related studies in those fields.

Figure 2.2 Research origin of BIM-related papers published



2.2.2.1 Research on Implementation of BIM in the Construction Industry

Over the past years, the architecture, engineering, and construction (AEC) industry has witnessed an accelerated diffusion of BIM, supposed to act as an emerging, promising, and innovative technology and process, dramatically transforming the way of a building from the original conception onwards to demolition (Hardin, 2011; Azhar et al., 2012). With the ever-accelerating adoption of BIM, the profitability, efficiency, relationship within related practitioners, are supposed to be improved through enhanced collaboration (Azhar, 2011).

In recent years, BIM is gradually being extensively adopted by construction professionals and practitioners in the process of effectively enhancing the design, construction and operation level throughout a building's lifecycle (Arayici et al., 2011a). As construction industry are being confronted with great challenges to improve productivity, efficiency, and profitability of construction projects (Arayici et al., 2011b), BIM is currently considered as a transformative information technology to achieve these goals. According to McGraw-Hill (2008) Construction Report, 35% of BIM users were reported to be very heavy users while 38% were light users. And the highest level of usage of BIM was supposed to grow rapidly to 45% in 2009, in which architects and owners were the heaviest users of BIM compared to the engineers and contractors. Also, McGraw-Hill (2009) indicated that nearly 39% of the construction industry of major projects in the USA were now utilizing BIM during the process of design and construction procurement. Additionally, in china over the past several years, the implementation of BIM has been growing rapid, especially amidst large companies that can capitalize best on its value, indicating that Chinese constructor has gradually perceived the great potential benefits of BIM adoption in construction projects (Bernstein, 2015).

Likewise, enhancing adoption of BIM is receiving continuous proliferation in academic articles. Gu and London (2010) pointed out that on account of various business incentives, such as the need for sustainable design and construction, integrated as-built database for facilities management, the adoption of BIM in AEC industry is particularly promising. They also established and developed a Collaborative BIM Decision Framework to facilitate BIM adoption through a Focus Group Interviews (FGIs) analysis. Singh et al. (2011) proposed a conceptual framework that specified the developed features and technical requirements of using BIM-server as a multiple disciplinary collaboration platform. The framework was significantly developed by utilizing focus group interviews (FGIs) on behalf of the various disparate AEC disciplines, case study of a specific project that exerted a state-of-art BIM server, and combined with a critical review and detailed analysis of existing collaboration platforms. They also found that the support technology requirements were of great importance in expediting technology management and adoption across disciplines. In addition, greater intelligent and automated collaboration support in design and construction can be achieved by promoting BIM-server investigation and development. Lu et al. (2012) proposed a generic model to practically identify and measure the benefits of BIM by comparing two learning curves, which can be used as a learning tool to promote the adoption of BIM. Porwal and Hewage (2013) also proposed a structured and collaborative BIM-based partnering framework for public procurement construction projects, in order to facilitate widespread adoption of BIM and maximizing the benefits out of BIM implementation. A BIM model can be widely used for multifarious purposes, e.g., virtually planning and design, construction scheduling, cost estimation, data integration, collision detection, and facilities management (Azhar et al., 2008; Schlueter and Thesseling, 2009; Azhar, 2011; Lu et al., 2012). Consequently, BIM is arguably perceived as an instrumental tool for mitigating the construction industry's scattered nature, enhancing efficiency, and lowering the high costs of inadequate collaboration (Succar, 2009; Lu et al., 2012).

As indicated by Bernstein (2015), in China, contractors are currently at higher adoption levels than architects. However, generally, the current utilization rate of BIM is still in a relatively infant stage. This was evidenced by the survey (CCIA, 2013), 85.05% of construction enterprises reported that they have not been involved in any BIM-based projects.

2.2.2.2 Research on General Benefits of BIM Implementation

As a term and method that is rapidly gaining popularity, BIM is under the scrutiny of many building professionals questioning its potential benefits on their projects (Barlish and Sullivan, 2012). The beneficial impacts of utilizing BIM have been broadly explored, like more efficient and effective process of sharing or modifying information, reduced costs, enhanced design quality, greater integrated data, decreased change orders, improved interoperability, and better life-cycle management (Howard and Björk, 2008; Barlish and Sullivan, 2012; Love et al., 2011c; Azhar, 2011). More specifically, BIM can store the entire design information into a share and open repository effectively to achieve integration and uniqueness of information. Also, synchronized information with regard to the construction schedule, cost, safety, and quality can be obtained by applying BIM in order to fully accomplish specified progress (Baoping et al., 2010). During the operation and maintenance stages, BIM can well control of all related information, such as physical and functional information, facilities performance, to regularly assess the status, thus to adjust the schedule in time to enhance management level in the process. Generally, BIM enables the production process more efficient, with tighter schedules, lower project costs, less rework, better collaboration among practitioners, as well as enhanced productivity (Farnsworth et al., 2015).

Despite widespread recognized benefits of BIM usage, users are supposed to take additional cost and time/schedule benefits into consideration (Lu and Li, 2011; Becerik-Gerber and Rice, 2010). For example, based on the 32 major projects that utilized BIM, the case studies conducted by Stanford University Center for Integrated Facilities Engineering (CIFE, 2007) indicated great beneficial consequences, like up to 40% reduction of unexpected change, more accurately cost estimation compared with traditional ones, up to 80% reduction in time taken to generate a cost estimate, up to 10% of contract value cut down through clash detections, and up to 7% reduction in project duration. Issa and Suermann (2009) performed a questionnaire survey revealed that quality, on-time completion, and units per labor-hour were explored as the top 3 benefits resulting from implementing BIM. Jung and Joo (2011) developed a comprehensive framework and evaluation methodology to quantify the overall benefits and effectiveness of BIM usage, with the purpose of identifying promising areas and driving factors for practical construction projects. The proposed framework served as a foundation to improve the communications with shared understanding. Barlish and Sullivan (2012) carried out a case study approach to provide a more comprehensive methodology to identify the benefits of BIM, as a result of more holistic and exhaustive framework for measuring benefits of BIM usage. Also, Love et al. (2013) established a benefits evaluation framework to obtain a wide range of benefits by incorporating intangible benefits and costs apart from return on investment.

2.2.2.3 Research on Limitations of BIM Implementation

Nevertheless, adoption of any emerging technology in any industry would pose challenges (Porwal and Hewage, 2013). Current work practices may need a great shift to better accommodate the changes brought by the application of new technology to facilitate collaboration and achieve better consequences (Cerovsek, 2011b; Gu and London, 2010). Specifically, it is not only a shift in technology implemented but also a tremendous adjustment or transformation to the existing practices that practitioners work (Porwal and Hewage, 2013). A mass of factors have been identified as the major factors hindering adoption of BIM, like lack of initiative and training chance, dispersed and complex features of the AEC industry, obscured roles, responsibilities, and distribution of benefits (Gu and London, 2010). In addition, technological obstacles for BIM implementation, with respect to the changes of organizational form and procurement processes, are also deemed as one of the major factors impeding widespread adoption of BIM. Also, sometimes, industry people are reluctant to make changes with existing work practice and hesitate to learn new concepts and technologies.

An effective approach of adopting a new technology is to encompass it in the contract as a mandatory condition by the client or owner, who has the ultimate decision-making power to determine the usage of BIM. However, public sectors often have concerns concerning the immature market and mechanism of utilizing BIM and are also afraid of diminishing competitive capability by increasing construction project costs with the implementation of BIM (Porwal and Hewage, 2013). Eadie et al. (2013) comprehensively investigated the reasons for not adopting BIM in construction projects via 92 surveyed practitioners that utilized BIM. Results implied that lack of expertise, lack of client demand, cultural resistance, and high investment cost were considered as the leading factors inhibiting BIM implementation. Table 2.2 summarized the barriers and limitations of BIM technology implementation, indicating that BIM implementation could be influenced and contained by multifarious factors, including but not limited to technological, organizational, or cultural issues.

Table 2.2 Summary of barriers and limitations on BIM implementation

Code	Barriers and limitations	Sources
BL01	High investment costs with lower rate of return on investment	Ku and Taiebat (2011), Porwal and Hewage (2013), Azhar (2011), Eadie et al. (2013)
BL02	Technological obstacles: lack of data and software interoperability	Taylor (2007), Gu and London (2010), Bernstein and Pittman (2004), Grilo and Jardim-Goncalves (2010), Ku and Taiebat (2011), Cerovsek (2011a), Porwal and Hewage (2013), Love et al. (2011c), Howard and Björk (2008)
BL03	Lack of industrial standards and guidelines in BIM implementation	Ku and Taiebat (2011), Eastman et al. (2011), Eastman et al. (2009)
BL04	Lack of statutory and normalized contractual agreements in distributing	Taylor (2007), Gu and London (2010), Bernstein and Pittman (2004), Grilo and Jardim-

	responsibilities, risk, and reward among contracting parties	Goncalves (2010), Ku and Taiebat (2011), Arayici et al. (2011b), Porwal and Hewage (2013)
BL05	Lack of trained and proficient professionals familiar with BIM implementation process and software	Gu and London (2010), Ku and Taiebat (2011), Arayici et al. (2011b), Eadie et al. (2013)
BL06	The resistance to change traditional practice and procurement method	Taylor (2007), Gu and London (2010), Grilo and Jardim-Goncalves (2010), Arayici et al. (2011b), Porwal and Hewage (2013), Eadie et al. (2013)
BL07	Lack of scientific and authentic studies quantifying the perceived value of BIM	Gu and London (2010), Arayici et al. (2011b)

2.2.2.4 Interoperability Issues

Due to the substantial different applications used by various practitioners, together with the diverse fragmental variables involved in the building construction projects, interoperability has become a great challenge that the AEC industry currently confronted with (Grilo and Jardim-Goncalves, 2010). To keep such information open and non-proprietary, it is necessary to develop and establish a standard platform, where different software package can communicate with each other. The value of interoperability on BIM was explored and evaluated by many research scholars.

As indicated by Grilo and Jardim-Goncalves (2010), in order to achieve integrated use of BIM technology, it is crucial for construction projects to enhance communication and coordination interactions between different players, thus to improve interoperability. They believed that BIM approach can facilitate to achieve efficiency and differentiation value levels, which means greater cost beneficial results and less risky outcomes by disposing of the need for interoperability in BIM. They also concluded that great emphasis should be placed on collaboration and channel interaction types of interoperability, which can facilitate BIM to achieve higher value level, i.e. value innovation. Arayici et al. (2011a) asserted that it is not a simple approach to learning a type of new software, but a paradigm shift to training staff, rearrange workflows and responsibilities and transform the way of modeling construction (Arayici and Aouad, 2010; Arayici et al., 2011a).

To facilitate data exchange between heterogeneous AEC software applications, the Industry Foundation Class (IFC) has been designed to sustain a wide range of BIM exchanges in the construction industry (Eastman et al., 2011; Venugopal et al., 2012). Despite its necessary to exchange modeling data, IFC alone is not a sufficient condition for achieving full interoperability between different building information modeling (BIM) software applications (Eastman et al., 2009). In order to achieve specific model view, a set of standardization efforts has been developed, such as Model View Definitions (MVD), which is required to specify exactly what types of information should be exchanged and in what form and structure the IFC schema are to be used (Venugopal et al., 2012).

2.3 Construction Productivity

2.3.1 Definition of Construction Productivity

Construction productivity has long been a concern in both industry and academia, for it can be improved to foster sustaining economic growth and generate substantial social wealth and welfare (Park et al., 2005; Kenley, 2014; Tookey, 2011). Being the most dominating factor contributing to the remarkable economic profitability of most construction projects (Yi and Chan, 2014; Kenley, 2014), productivity is receiving incessantly increasing concern with regard to the production efficiency of the whole construction industry. Nevertheless, there is no unified agreement on the definition of "productivity" (Yi and Chan, 2014; Thomas and Mathews, 1986) in both construction industry and academia. Additionally, it can be measured in diverse approaches determined by the application of specific domain, like an industry, an individual enterprise or just a concrete project. The *Merriam-Webster* definition of "productivity" is the rate at which goods are produced or work is completed. As stated by the *Oxford English Dictionary*, productivity is the state or quality of being productive. *Wikipedia* defines productivity as an average measure of the efficiency of production. To sum up, *productivity can be defined as the power of being productive, efficiency and the rate at which goods are produced.*

Generally, construction productivity is commonly and concisely expressed as the rate of output to its associated input in the production process. Thus, construction productivity can be regarded as an indicator measuring the effectiveness of construction production process denoted by the ratio of output obtained to input devoted. According to Chau and Walker (1988), productivity estimation that adopts one or more inputs or factors, but not all factors, is called partial productivity. A common example of partial productivity is labor productivity, usually expressed as output per hour. Despite its relatively simple concept to comprehend and express, labor productivity may be completely incorrectly in measuring resources utilization rate. An alternative term, for example, total factor productivity, where outputs and all identifiable inputs are considered, was applied by Chau and Walker (1988) to establish an operational framework for measuring construction productivity by utilizing diverse construction cost and price indexes at the industry level. Since this research aims to identify the relationship between BIM and construction productivity on project level, partial productivity with selected inputs is more appropriate for this research at project-level due to the fragmental and multiple variables involved.

2.3.2 Measuring Construction Productivity

The measurement of construction productivity is highly diversified based on the utilization of various purposes or sectors in the construction industry, ranging from evaluating economics state of a country to a specific type of craft or individual crew (Thomas et al., 1990). Hence, it is improper and inadequate to define or measure construction productivity simply exerting a single measure or meaning, even if accurate (Thomas et al., 1990; Bröchner and Olofsson, 2012; Ellis Jr and Lee, 2006). Numerous previous studies have been conducted concentrating on standardizing the measurement of construction productivity(Park et al., 2005; Oglesby et al., 1989). However, no identical and universal methods and norms have been achieved to measure construction productivity on accounts of intricate, fragmental and dynamic nature of uncertainties contained of construction projects (Chau and Walker, 1988; Oglesby et al., 1989; Park et al., 2005; Siriwardana and Ruwanpura, 2012; Hughes and Thorpe, 2014). Given a specific task or a change, construction productivity can be measured in various alternative approaches. Generally, three measurements are frequently applied in the construction industry in the literature (Oglesby et al., 1989; Arditi and Mochtar, 2000).

2.3.2.1 Activity Level

Firstly, an activity-oriented model which define productivity as labor productivity has been widely used by project executives and contractors to control and monitor field activities (Arditi and Mochtar, 2000). One may prefer a relatively easier way to measure construction productivity for detailed estimating or scheduling at the activity or site level. And it is unsurprisingly that labor productivity was perceived as one of the best indicators for measuring construction productivity. Being the focal point of construction industry, a plenty of past research efforts had been made on measuring labor productivity (Hanna, 2001; Hanna et al., 2005; Hanna et al., 2008; Allmon et al., 2000; Ellis Jr and Lee, 2006; Rojas and Aramvareekul, 2003a; Song and AbouRizk, 2008; Crawford and Vogl, 2006; Chau and Walker, 1988). For example, Thomas et al. (1990) performed a factor model together with expectancy theory model of motivation to model construction labor productivity. Song and AbouRizk (2008) developed a systematic method to measure and estimate labor productivity by exerting a consistent measurement system to quantify outputs and inputs, thus to establish a systematical system of acquiring data that synthesized and synchronized all historical and current projects' data. Then, a labor productivity model regarding steel drafting and fabrication activities was set up by using artificial neural work and discrete-event simulation modeling techniques. Siriwardana and Ruwanpura (2012) developed a Worker Performance Index (WPI) tool that integrated various different factors, such as management, supervisor assessment, motivation, and technical skills, to evaluate and examine the construction worker performance quantitatively, thus to improve construction productivity. Because of its labor-intensive characteristics, construction activity-level productivity can be generally perceived as labor productivity and is calculated as Eq. (2.1), defining output as work quantities installed and input as actual labor hours expended (Rojas and Aramvareekul, 2003a; Song and AbouRizk, 2008; Hanna et al., 2008).

Labor productivity = work quantity installed / actual labor hours (2.1)

It indicates the number of quantities installed per labor hour. Thus, higher values of productivity signify better productivity performance. Labor productivity can be useful for contractors in bidding and monitoring field activities.

2.3.2.2 Project Level

However, this aforementioned approach is insufficient and intricate as a typical representation of measuring global productivity values of construction projects, where diverse and fragmental variables are embraced (Mohammadian and Waugh, 1997). Consequently, Ellis Jr and Lee (2006) developed a project level productivity (PLP) method to measure construction productivity that included all project activities based on field data, uniformly quantified by the notion of an equivalent work unit (EWU) and total worker hours expended, and mathematically denoted as:

$$\text{PLP} = \text{total worker hours} / \text{total EWU} \tag{2.2}$$

This approach provides an opportunity for construction professionals to determine project performance by combining multitudinous continuous concurrent and correlated work items into PLP as a whole, regardless of units of measurement and types of work. For example, Park et al. (2005) proposed a feasible productivity data collection tool, named Construction Productivity Metrics System (CPMS), which classifies 56 measurement elements into seven categories envisaged to measure output directly based on the installed items, such as area, length, volume, or weight, for benchmarking aims.

But when it refers to the construction project as a whole, a more accurate measurement of construction productivity can be expressed as the project productivity index (PPI) (Hanna et al., 2005), as shown in Eq. (2.3), the ratio between actual total work hours performed and estimated or planned total work hours performed. While project-level productivity is on grounds of construction activities, this measurement rules out the differences between units of measurement and types of work by dividing the budgeted (baseline) work hours by actual work hours. The established benchmark or baseline can be utilized by projects managers and construction executives to trace the productivity changes or compare with other projects.

PPI = earned total work hours performed / actual total work hours performed (2.3)

A PPI less than 1 indicated that more work hours were needed to reach completion, whilst a more productive project would get a PPI greater than 1. Generally, higher PPI stands for the greater level of production efficiency (Hanna et al., 2005). This approach can be further developed and mathematically expressed as Eq. (2.4).

Productivity performance ratio (PPR) = Actual productivity / Expected productivity (2.4)

PPR is also a unitless measurement expressed as the actual productivity over baseline productivity (Thomas and Yiakoumis, 1987). It eliminates the difference between different job types.

2.3.2.3 Industry Level

It is undoubtedly that construction industry has commonly and frequently been perceived as the paramount and enabling indicator contributing to the sustainable growth of a nation’s economy. An economics method has been utilized to define construction productivity at the industry level, which can be expressed by economists and accountants as the total factor (multifactor) productivity (TFP), a more accurately expression: the ratio of total output production to its corresponding identifiable input resources (Chau and Walker, 1988; Thomas et al., 1990; Hanna et al., 2005; Hanna et al., 2008). As demonstrated in Eq. (2.4), total outputs and inputs can be both measured in dollars (Thomas et al., 1990; Arditi and Mochtar, 2000):

TFP = Total output / Total input = dollars of output / dollars of input (2.5)

where resource inputs include all determinants, namely tangible physical inputs, like labor, materials (raw materials and equipment), capital, investment, likewise intangible sectors, such as skills, management and technologies (Chau and Walker, 1988; Thomas et al., 1990; Arditi and Mochtar, 2000; Hanna et al., 2005; Hanna et al., 2008; Hughes and Thorpe, 2014; Crawford and Vogl, 2006). As pointed out by Chau and Walker, output is usually expressed as gross or value-added. For the construction industry, the concept of gross has been in common use due to the importance of intermediate inputs, such as new materials. Thus, gross product originating can be likewise adopted to express the output of a private industry (Rojas and Aramvareekul, 2003a). TFP can be used as an economic indicator to predict the economic status of a nation or a society or for governmental agencies carrying out decision-making policy (Thomas et al., 1990; Bröchner and Olofsson, 2012). Furthermore, it can also be applied to evaluate the industry trends or in contrast with other industry sectors (Council, 2006; Song and AbouRizk, 2008), such as manufacture sector.

Industry standard productivity measurements must first be set up to serve as a standard enforced in present practical work before substantial improvements and foreseeable benefits can be realized (CII, 2001; Song and AbouRizk, 2008). To improve productivity, a good system is needed to measure and track productivity so that the impact of productivity improvement efforts can be judged. In conclusion, previous experience reveals that no generally accepted productivity measurement standards are existing for estimation purposes. Productivity can be expressed and measured in various approaches from disparate perspectives by different people, in terms of the level of aggregation, the source of data, and the boundary of the production process, resulting in incomparable or ambiguous values (Chau and Walker, 1988). In this research, productivity performance ratio (PPR) was employed as the primary measurement method to evaluate the impacts of BIM on construction projects productivity.

2.3.3 Factors Affecting Construction Productivity

2.3.3.1 General Factors

Factors affecting construction productivity has been explored and certified by a multitude of scholars, for it is a prerequisite for improving productivity. It is unlikely to improve construction productivity without recognizing the influential factors that impact productivity (Mojahed and Aghazadeh, 2008). Additionally, factors affecting construction productivity can be dynamic, varying with diverse background and projects (Koehn and Brown, 1986). A survey carried out by Arditi (1985) indicated that productivity improvement should endeavor in enhancing marketing practices, planning and scheduling, labor management issues, site supervision, industrialized building systems, equipment policy and engineering design. Lim and Alum (1995) identified 17 factors impacting construction productivity, including management and manpower issues. Lacking skilled supervisors and workers and high rate of labor turnover were perceived as top three items affecting construction productivity in Singapore. Olomolaiye et al. (1998) classified factors into two categories, internal (management practice, technology, labor skills, and training) and external (design, environment, changes made by the client, economic development level, and political social stability) respectively. Arditi and Mochtar (2000) analyzed the findings of surveys of the top 400 US contractors and concluded that five major points: cost control, scheduling, design practices, labor training, and quality control respectively, were deemed as of great importance to impede construction productivity. Makulsawatudom et al. (2004) identified ten most influential factor affecting construction productivity of Thailand, namely in order, material shortage, incomplete drawing, lack of professional supervisors, ineffective tools and equipment, absenteeism, insufficient communication, instruction time, poor site layout, inspection delay and rework. Hughes and Thorpe (2014) investigated top 15 factors ranked by relative importance index that influenced construction productivity. Three major factors, that is, rework, poor supervisor competency and incomplete drawing, were perceived most likely to affect construction productivity. Issa and Suermann (2009) conducted a survey based on six primary construction key performance indicators commonly used in the construction industry: quality control (rework), on-time completion, cost, safety, dollar/unit performed, and units per man hour. Results showed that quality, on-time completion, and units per man hour were the highest ranking KPIs responses preferred. Chelson (2010) also ascertained that key indicators of productivity improvement could be placed on the amount of request for information (RFI), rework reduction, schedule compliance, and change orders due to design and construction interferes. Specific factors will be presented in the next section and Table 2.3 summarizes related publications of factors affecting construction productivity.

2.3.3.2 Specific Factors

Manpower Factors

Because of its labor-intensive feature, project-level construction productivity could be greatly influenced and determined by construction labor productivity. As indicated by Rojas and Aramvareekul (2003b) and Lim (1996), the improvement of labor productivity has become one of the major approaches contributing to the profitability of construction industry.

Much of previous research has been investigated to identify the improvement drivers of labor productivity. For example, Yi and Chan (2014) presented a state of the art review on construction labor productivity from different levels, namely, industry, project, and activity. Major research areas like factors affecting labor productivity are identified and future research trends are proposed. A recent survey conducted by Rojas and Aramvareekul (2003b) demonstrated that management skills, such as strategic management, procurement management, and manpower issues, like improving training programs, enhancing worked motivation, had substantial room for labor productivity improvement. Hanna et al. (2008) also pointed out that the appropriate use of shift work was critical, seeing that it may, if used improper, have detrimental to construction labor productivity. Hinze (2011) noted that both additional working days and increased workforce could decrease labor productivity. Mojahed and Aghazadeh (2008) maintained that skills and experience of the workforce, management, job planning, workers' motivation, and material availability, were the major concern of improving productivity by implementing related index technique. Further analysis indicated that skills and experience of the workforce would be confronted with greater challenges because of lacking skillful labor.

Rework

Rework is frequently regarded as an unexpected process of redoing works or activities that are inaccurately or inappropriately enforced in the previous stage (Hughes and Thorpe, 2014). A diverse sort of factors, such as omissions and errors, design changes, inefficient management, failures may result in rework, which could affect the productivity of construction projects in adverse.

Former research demonstrated that cost of rework (quality) could be quite high in terms of overall project costs. For example, Barber et al. (2000) developed a methodology to measure the cost of quality failures of typical projects, which were identified to occupy a considerable percentage of total cost. The case study of two projects conducted by Love and Li (2000) maintained that cost of rework could account for 3.15% of project contract value increase. Findings also suggested that omissions and errors, design changes resulting from inadequate design, insufficient coordination, poor communication (Hwang et al., 2009), were the major causes contributing to rework. Love (2002) revealed that 52% of cost overruns could be attributed to rework, which could in turn account for 10% to 15% of contract value (Sun and Meng, 2009).

Technology Factors

Although previous views indicated a technologically stagnant industry (Zhai et al., 2009; Goodrum et al., 2010), the implementation of advanced technology has been of great concern concerning improving construction productivity. Allmon et al. (2000) insisted that, generally, a positive relationship can be explored between technology innovation and productivity enhancement. For example, as pointed out by Zhai et al. (2009), information technology had a positive impact on enhancing automation and integration of information systems, of which higher level means greater improvement in construction productivity. A study was conducted by Goodrum and Haas (2002), through examining 200 construction activities over a 22 years duration at the activity level. As a result, advanced equipment technology gave rise to a greater improvement in productivity over that of partial factor productivity. A similar survey was conducted by Goodrum and Haas (2004), which realized significant long-term improvement in construction productivity through promoting equipment technology. By analyzing 100 construction activities from 1977 to 2004, Goodrum et al. (2009) found that significant improvement in material technology can be an effective approach to enhancing both labor and partial construction productivity. Another research conducted by Grau et al. (2009) indicated that materials tracking technology can dramatically improve the craft labor productivity. Hewage et al. (2008) ascertained that enhanced usage of information technology could greatly improve on-site communication between managers and workers, as well as worker satisfaction.

Time/Schedule

Completing projects within prescribed time can be a commonly recognized indicator of project efficiency. However, the incremental proportion of construction projects is suffering from serious time overruns by now. For example, Siriwardana and Ruwanpura (2012) pointed out that frequent and extensive delays of a project can be the dominating contributor to the construction productivity losses. Any delays or extension of time would probably result in prolonged project duration, usually companied by lower productivity and higher construction cost. As indicated by Assaf and Al-Hejji (2006), change order was identified to be the major factor causing delays of large construction projects.

Shift work or extended overtime can also be one of the efficient approaches to accelerate the schedule, thus to improve productivity. Adrian (1987) revealed that arranging more difficult and complex construction works in the mornings over afternoons had greater beneficial impacts of productivity improvement regarding shift work to accelerate scheduling. Research into extended overtime of labor intensive trades was also explored by Hanna et al. (2005), which indicated a negative rate of labor productivity increase.

Cost

In general, lower cost usually results from higher construction efficiency that fully utilizes all the resources involved. Greater prospective profitability could be realized by the increasing revenue as a consequence of lower project cost. Accompanied by the unceasing incremental scale and complexity of construction projects (Tucker, 1986; Chan et al., 2004), as pointed out by Siriwardana and Ruwanpura (2012), cost overruns have been perceived as one of the primary factors affecting construction productivity. For example, in recent years, construction costs have increased at a disproportionate ratio compared with the rate of inflation (Tucker, 1986; Oglesby et al., 1989; Arditi and Mochtar, 2000). Tucker (1986) indicated that construction labor costs, assumed to be 33-50% of overall project costs (Hanna, 2001; Hanna et al., 2005; Hanna et al., 2008; Siriwardana and Ruwanpura, 2012), was deemed as the main and major cause that resulting in the project overspending. As indicated by Kaming et al. (2010), the paramount causes of time and cost overruns were design changes, poor labor productivity, inadequate planning and lack of resources.

Management factors

As stated by Tucker (1986), due to its increasing scale and complexity, the collaboration and coordination of all practitioners, including owners, contractors, consultants etc., has become the greatest challenge for construction projects. According to Tucker (1986), for purpose of improving construction productivity, focused attention should be paid to management issues that enhance communication with construction practitioners. Large amounts of opportunities can be found in project orientation, planning, communication, design, technology, etc. Abdel-Wahab et al. (2008) also pointed out that efforts should be focused on organizational management practice to facilitate further improvement of productivity of the UK construction industry. Rivas et al. (2010) revealed that rational plan and arrangement of materials, tools, and equipment were the major factors affecting construction productivity. Also, as identified by Dai et al. (2009), the availability and management of jobsite materials, tools, and equipment could have tremendous impacts on labor productivity.

Table 2.3 Summary of Related Publications of Factors Affecting Construction Productivity

Authors	Labor Productivity	Rework	Time	Cost	Technology	Management

Naoum (2016)	*	*			*	*
Yi and Chan (2014)	*					
Hughes and Thorpe (2014)		*		*		*
Siriwardana and Ruwanpura (2012)	*		*	*		
Hinze (2011)	*		*	*		
Liu et al. (2011)	*					
Rivas et al. (2011)	*	*				*
Diekmann and Heinz (2001)	*					
Dai et al. (2011)	*					
Jarkas and Horner (2011)	*					
Goodrum et al. (2010)					*	
Kaming et al. (2010)			*	*		
Mawdesley and Al-Jibouri (2010)						*
Dai et al. (2009a)	*					*
Dai et al. (2009b)	*					*
Zhai et al. (2009)					*	
Hwang et al. (2009)		*	*	*		*
Eastman and Sacks (2008)	*				*	
Song and AbouRizk (2008)	*					

Hanna et al. (2008)	*					
González et al., 2008	*					
Hewage et al. (2008)					*	*
Abdel-Wahab et al. (2008)	*					*
Mojahed and Aghazadeh (2008)	*					*
Kazaz and Ulubeyli (2007)	*					
Crawford and Vogl (2006)	*	*			*	*
Assaf and Al-Hejji (2006)			*			
Ezeldin and Sharara (2006)						
Hanna et al. (2005)	*		*			
Horman and Thomas (2005)	*					*
Fayek and Oduba (2005)	*					*
Ng et al. (2004)	*	*	*			*
Makulsawatudom et al. (2004)		*	*		*	*
Goodrum and Haas (2004)	*				*	
Rojas and Aramvareekul (2003b)	*	*	*			*
Rojas and Aramvareekul (2003a)	*					
Ballard et al. (2003)			*			*
Cox et al. (2003)	*	*	*	*		*

AbouRizk et al. (2001)	*					
Barber et al. (2000)		*		*		*
Love and Li (2000)		*		*		*
Goodrum et al. (2002)					*	
Goodrum and Haas (2002)					*	
Allmon et al. (2000)	*				*	*
Arditi and Mochtar (2000)	*	*	*	*		
Hanna et al. (1999a)	*	*	*			
Hanna et al. (1999b)	*	*	*			
Hanna et al. (1999c)	*	*	*	*		
Lim (1996)	*					
Lim and Alum (1995)	*					*
Thomas et al. (1990)	*					*
Oglesby et al. (1989)				*		
Adrian (1987)	*		*			
Koehn and Brown (1986)	*					
Tucker (1986)	*			*		*
Arditi (1985)	*					*
Maloney (1983)	*					*

2.4 Chapter Summary

This chapter first explores the various definition of building information modeling and gives an overview of BIM-related publication in target journals. The current adoption of BIM and general benefits of BIM implementation in the construction industry have been comprehensively reviewed and identified. Interoperability issues and limitation of BIM in the construction industry have also been discussed. Then, construction productivity has been reviewed based on selected paper from well-known academic journals in construction management. A comprehensive definition of construction productivity from different perspectives has been developed. Primarily used measurements have been reviewed in measuring construction productivity. Finally, factors influencing productivity has been explored and identified by inclusive literature review.

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

This chapter firstly provides an overview of how the research is conducted, as well as the research process in detail. Then a comprehensive review of research methods and analysis techniques employed in this research are introduced.

3.2 Research design

3.2.1 Research Approach

To identify the research problems and achieve the four specific research objectives presented in Chapter 1, the research framework is well-designed by combining qualitative and quantitative methodologies, applying appropriate research methods and data analysis tools, formalizing a logical research process.

This research aims to identify the relationship between BIM implementation and construction productivity both in design and construction stage. Through literature review, research gaps, as well as the related definition and basic features of construction productivity and BIM, were identified in Chapter 2. Then, by a subsequently further document analysis, a design error reduction model and BIM-enabled construction productivity gains model have been developed in Chapter 4. Chapter 5 assessed the impacts of BIM implementation in reducing design error, validate the conceptual model based on the different design error reduction (DER) indicators, as established in Chapter 4. Finally, the identified influential factors regarding construction productivity were utilized to test the proposed model with the aim of exploring how the BIM-enabled factors affecting project-level construction productivity, as analyzed in Chapter 6. The research framework for achieving these four objectives is shown in Figure 4.1.

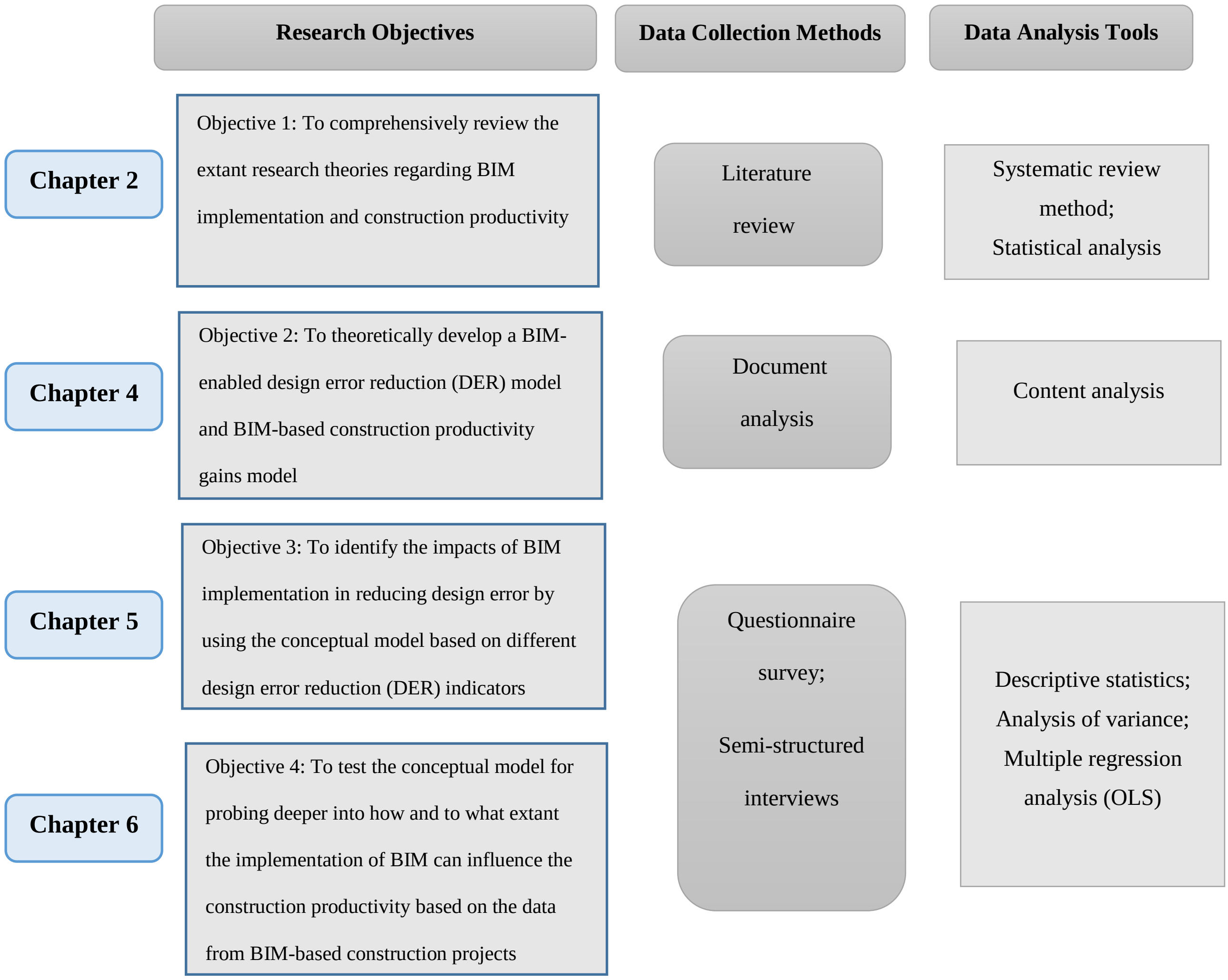


Figure 3.1 Research Framework

3.2.2 Qualitative research and quantitative research

It is believed that the study of positivist epistemology (theoretically grounded) principally holds the assertion that the existence of a priori fixed relationships within phenomena could be typically and structurally investigated, in an attempt to advance foreseeable perception of a phenomena or theory (Orlikowski and Baroudi, 1991). Hence, the research problems addressed by positivists reveal the need to determine and evaluate the causal relationships among variables, whereby causes determine or influence outcomes (Creswell, 2013). Since this study aims to increase the body of knowledge concerning the relationship between BIM implementation and construction productivity, positivist research methods are appropriately applied.

Research approaches are schemes and procedures for research that follow the steps from expansive assumption to specific methodology of gathering, analyzing, and interpreting data (Creswell, 2013). *Chambers English Dictionary* defines research as a process of conducting a careful search and systematic investigation in order to increase the stock of knowledge (Fellows and Liu, 2015). The *Concise Oxford Dictionary* extensively proposes a broader definition of research as an endeavor to perform the systematic, scientific, and critical investigation into the extant or previous study of materials, sources of a subject towards the foundation of facts and conclusions, devising new applications (Fellows and Liu, 2015; Creswell, 2002). The purpose of the research process is to generate a new perception of knowledge or deepen understanding of a specific topic or issue (Neuman, 2002; Kothari, 2004). Qualitative research and quantitative research are generally perceived as two primary approaches of empirical research methods, that are fundamentally differentiated in data collection and analysis methods (Fellows and Liu, 2009).

With the intention of achieving the research objectives, qualitative research approaches that are drawn on observations, documentary analysis and interviews taken from real world modeling projects aim to investigate a question without attempting to quantifiably measure variables or identify potential relationships between variables (Creswell, 2002; Tashakkori and Teddlie, 1998). It is viewed that qualitative research methods could be beneficial for developing new theoretical thoughts and giving explanations of a phenomenon (Fellows and Liu, 2015). Generally, qualitative research is employed as a method of exploratory research as a basis for later quantitative research hypotheses. A quantitative research approach involves a systematic empirical investigation of the phenomena and quantifying their relationships among variables through a rigorous data analysis techniques. The primary data collection methods of quantitative research are drawn on experimental, correlational, and survey approaches (Creswell, 2002). These methods produce results that are easy to summarize, compare, and generalize. Statistics derived from quantitative research can be used to establish the existence of associative or causal relationships between variables, which are consistent with the philosophical and theoretical stance of positivism.

In either qualitative or quantitative research, the researcher(s) may collect primary or secondary data. Primary data is data collected specifically for the research, such as through interviews or questionnaires. Secondary data is data that already exists, such as census data, which can be re-used for the research. It is good ethical research practice to use secondary data wherever possible. In accordance with positivist methodology, this research employs quantitative data collection and analysis methods to empirically test the established research model.

3.3 Research Methods Adopted

As evidenced by Kothari (2004), research methods indicated that the behaviors or tools applied to choose and develop research techniques while research techniques refer to those detailed operations we apply to record data, process data, analyze data and so forth (Kothari, 2004). In order to achieve related research objectives, several research methods will be adopted during the research process.

3.3.1 Document Analysis

Document analysis is envisaged to address research problems and questions by investigating a variety of recorded information and published documents, incorporating academic publications, industry reports, and reports by international organizations, either digital or printed (Patton, 1990). As summarized by Bowen (2009), the primary sources of document analysis are diverse sorts of documentation, including background papers, books and brochures, journals, newspapers, and so forth. Document analysis can supplement the information obtained through other methods, such as interview and questionnaire survey under certain circumstances (Bell, 2014). Generally, document analysis is the principal qualitative method for in-depth content analysis and systematic review of existing data, which can be grouping into two approaches in detail based on the origins of data sources, namely, content analysis and existing data analysis. Content analysis is defined as any technique for acting inferential processes that objectively and systematically review and identify references from a theoretical perspective (Holsti, 1969). In this study, literature review is the major form of such analysis to collect background information of a research study. Literature review is a frequently used methodology applied to systematically review and consolidate the extant knowledge, research findings, theoretical and practical contributions in a certain research domain based on secondary sources (Merriam, 1998). It could help researchers to explore research problems of extant works with the aim of setting up a theoretical foundation for the current research and identifying knowledge gaps. In this research, a comprehensive review of construction productivity and the implementation of BIM has been conducted. Research gaps were identified and summarized to initiate the research objectives, serving as a solid foundation for future analyses. Official publications and reports were reviewed to explore existing achievements in the current construction practice. Existing data analysis in this study encompassed the collection and descriptive analysis of time-series data in public available statistical yearbooks.

The advantages of document analysis were identified by Caulley (1983). First, document analysis is the most efficient way of collecting certain types of data, such as background information and it also can collect some types of retrospective data. Besides, information obtained from documents is more reliable than that of observations and interviews, because people may be unwilling to provide certain information. In addition, document analysis is more convenient to perform than questionnaires, interviews, and observations. Finally, document analysis is an inexpensive and time-saving method to collect data implying research trends.

3.3.2 Questionnaire Survey

It is generally believed that survey could be the most commonly-used method in the fields of construction management, as samples of data could be gleaned from a large population in a standardized form (Saris and Gallhofer, 2007). As stated by Mangione (1995), surveys are a comparatively inexpensive way of collecting data by allowing respondents to have enough time to fill out the questionnaire and make inquiries if needed. Besides, it can keep confidential information from respondents, and responses could be evaluated in a relatively short time. In addition, respondents could fill out the questionnaire at their early convenience and provide adequate time allowing respondents sufficiently perceive the context of a set of questions.

The questionnaire survey is an effective instrument for conducting empirical research for collecting quantitative data without the physical reach of the respondents with the purpose of selecting the answers from target respondents in a standardized form. Standardized data could be derived from respondents by providing them a series of choices for any single question. The design of questionnaire should avoid any ambiguous and complicated expressions and be effortless to understand and answer (Oppenheim, 2000). The merit of conducting questionnaire surveys is to obtain a large amount of quantitative data, providing sources of investigating and synthesizing the major findings. However, the quality control of the data becomes difficult.

In this research, a questionnaire survey was utilized to solicit the professional views of the proposed models. Respondents were asked to rate the level of agreement on the importance of each separate items based on a five-point Likert scale (**1** indicates "**strongly disagree**" and **5** indicates "**strongly agree**"),

3.3.3 Semi-structured Interview

An interview can be described as a conversation with a purpose (Bingham and Moore, 1924). Dane (1990) defined an interview as *a structured conversation used to complete a survey*, in which the survey devises the structure of the conversation with the purpose of data collection. It can be conducted in different ways, such as face-to-face interviews, telephone interviews, and mail surveys. When the inquiries/questions regarding the research topic are addressed, a well-structured interview is one of the most effective ways to collect firsthand data if only interviewees can respond based on an accurate understanding of the questions. Among the various interview types, expert interviews, in which the interviewees are experts or experienced practitioners within the research areas, is an effective and widely used means to directly collect the in-depth, practical and up-to-date information.

Semi-structured interview is a method of research adopted most often in qualitative research (Longhurst, 2003). It is an information interchange process where interviewers aim to elicit useful and meaningful information from interviewees by asking informal and open-ended questions in order to develop a keen understanding of the relevant determined topic and bring about the opportunity for unfolding innovative new ways of perceiving and comprehending particular topic predetermined (Cohen and Crabtree, 2006). In the present study, this method was used to optimize and finalize the key factors/criteria which were tentatively identified by literature review and document analysis, and dig out practical problems existing in the current research process.

3.4 Facilitated Data Analysis Techniques

3.4.1 Descriptive Statistics and Analysis of Variance

Useful information cannot be extracted unless raw data collected from various samples is well organized (Russo, 2004). Therefore, descriptive statistics that can organize, summarize, simplify, and interpret data sets effectively should be used to analyze the sample data (Lee, 2008). In this research, descriptive statistical techniques were applied to quantitatively describe or summarize features of a dataset in order to identify the characteristics of particular groups and describe the similarities and differences among variables. Central tendency such as mean value, and measures of variability such as standard deviation were generated. Analysis of variance (ANOVA) was performed to provide a statistical test of whether the mean differences of the multiple groups were significantly associated with each other. In addition, ANOVA test could disclosure how demographic variables influence participants' responses.

3.4.2 Mean Score Ranking Technique

Ranking the relative importance of each variable was established by the "mean score" method. Rankings of various influential factors were obtained by calculating the means for the overall sample as well as for separate groups of respondents. If two or more factors happened to have the same mean value, the one with lower standard deviation was assigned a higher rank.

3.4.3 Multiple Regression Analysis

Regression analysis, perceived as the most broadly and frequently adopted statistical technique, is a robust instrument for investigating and modeling the causal relationship among variables (Efroymson, 1960). This instrument can be applied in various research fields, such as social sciences, economics, engineering, management sciences, physical sciences, and so forth. Multiple regression analysis is the most common form utilized to evaluate and analyze the relationship between a single dependent variable and several independent variables (Edwards, 1985). It describes the process of how the typical value of the dependent variable varies while the independent variable alters. Also, it helps to establish a mathematical equation used to measure the proposed model being investigated. The adjusted coefficient of determination (adjusted R^2) has been widely recognized as a measure to evaluate the goodness-of-fit of the regression model. It judges the fit of proposed model by the comparison of different regression equations with different number of independent variables or sample sizes (Srivastava et al., 1995).

It is of great significance to select and combine appropriate predictive variables to evaluate the dependent variable while addressing a large number of potential explanatory independent variables. Stepwise regression is regarded as a powerful instrument for automatically determine the best combination of potential predictive variables that best fits the dependent variable (Efroymson, 1960; Kutner et al., 2004). The variable selection process terminates when all variables fit the criterion to stay in the model and no variables outside the model fit the criterion to enter.

3.5 Chapter Summary

This chapter first describes the research design. Then, the major research methods, including document analysis, questionnaire survey, and expert interview, are discussed in details. The subsequent data analysis tools are introduced. In this research, a mixed research methodology, incorporating qualitative and quantitative research methods, was deployed to achieve research objectives.

CHAPTER 4 THE IMPACTS OF BIM IMPLEMENTATION ON CONSTRUCTION PROCESS: A CONCEPTUAL FRAMEWORK

4.1 Introduction

This chapter aims to review the impacts of BIM implementation in reducing design error during the design stage from literature with the aim of establishing a conceptual design error reduction framework with respect to the causal relationship between the impacts of BIM implementation and construction productivity in the construction stage.

4.2 Reduction of Design Error during Design Stage

4.2.1 The Desirability of Reducing Design Error in Construction Projects

The term ‘error’ could be defined as the occurrence of unexpected, erroneous or deviated outcomes when carrying out a particular assignment or towards the desired goal (Reason and Hobbs, 2003). As stated by Reason (2000), “it is not a cause of an event, but a symptom of a much deeper problem within a system”. The concept of design errors, also known as design deviations, are inherently defined as the errors, omissions, or changes arising from the design process (Burati Jr et al., 1992). With the increasing complexity of building construction projects, design errors are generally criticized as the major contributor to the failure of buildings and other civil engineering projects (Lopez et al., 2010; Lopez and Love, 2011), quality defects (Josephson and Hammarlund, 1999; Sun and Meng, 2009), accidents (Lopez and Love, 2011; Lopez et al., 2010; Rasmussen et al., 1990), lower productivity (Abdul Kadir et al., 2005), as well as the cost overruns and schedule delays of construction projects (Love, 2002; Love et al., 2010; Sun and Meng, 2009; Al Hattab and Hamzeh, 2015). Omissions or errors generated in the design phase may have severe impacts on later stages, such as construction and operation, along with the overall project performance (Al Hattab and Hamzeh, 2015). For example, Linderoth et al. (2014) stated that the cost of design errors can be as high as 26% of the total cost as a result of deficiency, which in turn incorporated 2-9% of production cost in building and construction projects. A similar study conducted by Burati Jr et al. (1992) suggested that design errors accounted for 79% of total deviation costs, with a subsequent 9.5% of total project budgets. Lopez and Love (2011) carried out a study by adopting questionnaire survey received from 139 projects. Results showed that the mean direct and indirect costs of design errors were explored to be 6.9% and 7.4%, respectively. Barber et al. (2000) also revealed that design errors contributed to 50% of costs with respect to quality failures in civil engineer projects. These results indicated that design error costs were substantially proportioned within overall project costs. Subsequently, once design errors are determined reworks or change orders are inextricably entailed to rectify or repair them that has occurred in order to match the desired requirements (Lopez and Love, 2011), which result in schedule growth, poor productivity with low profitability (Thomas and Napolitan, 1995; Ibbs, 1997; Hanna et al., 2002; Moselhi et al., 2005; Bower, 2000; Love et al., 2014). Sun and Meng (2009) reported that the cost of rework can result in 10-15% of contract value in construction projects. Hanna et al. (1999) quantified the impacts on labor efficiency by collecting data from 43 projects. The results of statistical analysis showed an evident increase in time elongation and subsequent decrease in labor efficiency. The adverse relationship between the number of rework and productivity was also identified by Ibbs (1997) and Manzoor Arain and Sui Pheng (2005). Bryde et al. (2013) also stated that construction quality can be immensely improved by a more accurate integrated process of design and documentation.

Driven by the presence and severity of design error, consequently, design errors are automatically perceived as a problematic issue and plague required to be addressed in construction projects (Al Hattab and Hamzeh, 2015). Numerous previous studies had been preoccupied with the causes and prevention strategies of design errors, with the purpose of attempting to build defenses to avert errors or mitigate their effects (Lopez et al., 2010; Love et al., 2014; Al Hattab and Hamzeh, 2015). Love et al. (2011c) established a systemic framework for error containment and reduction, and proposed a set of organizational and project defense strategies to minimize their occurrence. The impacts of organizational practices and project management strategies on reducing design errors were also emphasized by Love (2002). As stated by Love et al. (2010), if error reduction is evidenced as a primary performance indicator by owners, due to these great beneficial incentives, the occurrence of errors could be substantially decreased in construction projects by demanding relatively enforceable terms bound into contracts with the aim of improving the quality of contract documentation.

4.2.2 BIM-based Design Error Reduction Model

Numerous previous researchers have investigated the attributable factors affecting design error (Josephson and Hammarlund, 1999; Love et al., 2012; Love et al., 2011c; Lopez et al., 2010), attempting to seek out effective strategies to prevent or mitigate design errors (Love et al., 2008; Busby, 2001; Love et al., 2012). Managerial factors (e.g. adverse behavior, ineffective coordination and integration, inferior constructability) and organizational factors (e.g. inexperienced personnel, insufficient information and knowledge sharing pattern, inadequate quality assurance) were identified to be the principal factors influencing design errors (Lopez et al., 2010; Love et al., 2012; Love et al., 2011b). Prevention strategies, such as a system dynamics model, had also been developed by Love et al. (2000), which can enable designers and managers effectively manage the process of design documentation, thus to ameliorate design errors. It is believed that BIM is the most frequently conceived of as a powerful tool for visualizing and coordinating AEC work, thus to predict collisions, avoid errors and omissions (Zuppa et al., 2009). However, rare research had been placed on measuring and quantifying the impacts of BIM implementation in reducing design error. Thus, this chapter aims to thoroughly assess the effects of BIM in reducing design error, as well as develop a design error reduction model.

BIM has been evidenced by many researchers as an effective means for facilitating design processes (Eastman et al., 2008; Son et al., 2015; Sacks et al., 2010b; Sacks et al., 2010a; Taylor and Bernstein, 2009), reducing design error (Linderoth et al., 2014; Love et al., 2011c; Rajendran et al., 2013), thus to achieve productivity gains (Sacks and Barak, 2008). For example, Baoping et al. (2010) pointed out that the implementation of BIM could effectively integrate various professional design information, and sufficiently boost the ability to share and reuse this information. Research efforts to date also demonstrated that BIM had the ability to facilitate information sharing and enhance communication among project practitioners, and furnish innovative solutions for better design (Fan et al., 2014). As evidenced by Eastman et al. (2008), BIM made it possible for all the parties participating early in the projects and simultaneously addressing the design information with the purpose of shortening the time and reducing errors/omissions. Al Hattab and Hamzeh (2015) proposed a novel design error management strategy by applying social network theory and agent-based simulation, which was concentrated on team structures, interaction mechanics, and error diffusion dynamics with the aim of proffering underlying beneficial outcomes of integrating BIM and lean in design error reduction and diffusion containment. The combination of BIM and lean management theory in construction was also employed by Tauriainen et al. (2016) to improve the design management process. As indicated by Sacks and Barak (2008), BIM is particularly highly valuable at the early stages of design, which will directly contribute to a productivity gain in design documentation. Sacks and Barak (2008) found that the potential productivity gain can be achieved ranging from 15% and 41% of the hours required for a project in the drawing phase. Li et al. (2014b) presented and analyzed five comparable large-scale projects in different phases of lifecycle under various circumstances, to demonstrate productivity improvement due to the adoption of BIM enabling easier sharing and integration of information and convenient collaboration.

However, rare empirical research has been placed on quantifying the impacts of BIM on design error reduction, and quantitatively measuring the extent to which attributable factors could have the better ability to contain design error. This chapter first developed a conceptual framework of BIM-based design error reduction (DER) model based on the data from literature review, as shown in Fig 3.1. Specific factors were reviewed and described in the following section.

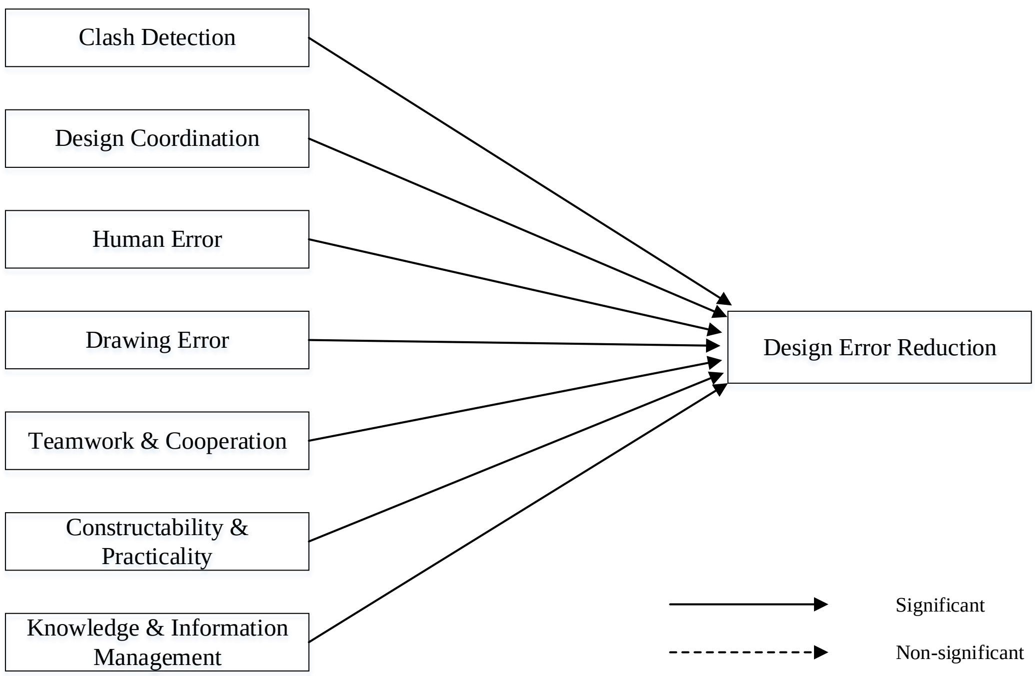


Figure 4.1 Conceptual framework of design error reduction model via BIM

4.2.2.1 Clash Detection

Clash detection can be the most effective means for time and cost saving by using BIM. Conflicts, which may give rise to inconsistencies and disputes of design, could be identified before the building was actually constructed, hence to facilitate coordination between designers and contractors (Eastman et al., 2011). As stated by Azhar (2011), BIM technology could be primarily used as a virtual instrument to identify latent collisions or clashes among a variety of structural, mechanical, electrical, and plumbing systems. Early detection via the BIM model in the design phase could be beneficial for error reductions, with consequent cost and schedule savings. In addition, clash detection could be an efficient way to accelerate the construction process, reduce project budgets, minimize errors and yield a better construction process (Eastman et al., 2008).

4.2.2.2 Design System Coordination

Design coordination could be perceived as the major strengths of implementing BIM in the early design stage by integrating and coordinating all the design systems with the goal of avoiding conflicts. A conceptual framework proposed by Wang et al. (2013b) denoted that BIM could be utilized as a practical tool for integrating facility management (FM) works into early design stage with the intention of consolidating collaboration between design team and FM team, thus to reduce modifications. As indicated by Eastman et al. (2011), the application of BIM can coordinate all the design systems of a building, and synthesize them into one model. To facilitate data exchange among different design systems, BIM can be utilized as an effective tool where different software package can communicate with each other (Grilo and Jardim-Goncalves, 2010), thus to enhance interoperability and design system coordination.

4.2.2.3 Human Error

Design consultants always ascertained that the implementation of BIM could enhance the quality of the documents by reducing human error as well as motivating architects to facilitate the building process from a virtual finalized project model in the design stage (Software, 2008). Reduced human error could yield the better ability to decrease mistakes or omissions which would arise design error and subsequent schedule growth (Love et al., 2011). A bad apple theory of human error proposed by Love et al. (2011a) was regarded as latent conditions contributing to errors. A systemic model was further developed with the aim of aiding BIM in reducing these errors.

4.2.2.4 Drawing or Document Errors/Omissions

BIM can be utilized as a tool for efficiently simulating and analyzing design drawing and documents with the purpose of reducing incomplete, incorrect, and remiss drawings or documents (Azhar, 2011). Four detailed case studies that utilized BIM were analyzed by Kaner et al. (2008), revealing certain amelioration in design quality due to error-free drawings. Sacks (2004) explored that the cost of drafting could be reduced by approximately 80-84% through the 3D parametric modeling. Another research carried out by Sacks and Barak (2008) suggested that the underlying productivity gains from 3D modeling could be ranged from 15% to 41% of the time requisite for drawing outputs. Bernstein et al. (2012) also indicated that the production cycle of design process could be substantially diminished by applying BIM in reducing document errors and omissions. Any design changes incorporated in the BIM model could be automatically updated, resulting in less rework by reducing drawing errors and omissions (Eastman et al., 2011; Rajendran et al., 2013).

4.2.2.5 Teamwork and Cooperation

The successful implementation of BIM allows all project stakeholders engaged in the early design phase with the purpose of enhancing communication and collaboration compared with the traditional processes (Azhar et al., 2012). As the diffusion of BIM implementation accelerates, collaboration among project practitioners should be promoted. A case study reviewed by Aranda-Mena et al. (2009) implied that the implementation of BIM can increase the confidence of design processes, improve co-ordination between various practitioners, thus to reduce rework and enhance the functionality of design. Rajendran et al. (2013) also stated that BIM have the ability to provide visible connections among project practitioners so as to foster design process and faster collaboration. Meanwhile, synchronized information with respect to construction time, cost and quality could be afforded in the BIM model with the aim of achieving common objectives (such as error reduction) within all participants (Baoping et al., 2010; Wu and Issa, 2013).

4.2.2.6 Constructability and Practicality

It is believed that BIM technology will substantially elevate the efficiency and effectiveness of delivery processes and the constructability of a facility (Sacks et al., 2010b; Rajendran et al., 2013). Bynum et al. (2013) ascertained that the capability of applying BIM to virtually constitute a building prior to constructing the real-world building yields an operative approach to examine its constructability in the real projects and to address any indeterminacies or discrepancies during the design process. This resulted in more efficient work of advancing design process and decreasing design errors. Also, the digital and computable data could be easily utilized by project teams to enhance the constructability and practicality of construction projects (Azhar, 2011), as well as promote cooperation and coordination of all project participants (Rajendran et al., 2012).

4.2.2.7 Facilitate Knowledge and Information Sharing

Knowledge and information could be interchanged and applied among construction practitioners and site engineers to discover and alleviate problems on site and decrease the time and cost of addressing matters related to constructability (Benjaoran and Bhokha, 2009; Ho et al., 2013). As ascertained by Linderoth et al. (2014), BIM can perform a vital role in facilitating knowledge, information, and expertise sharing in order to prevent design errors. Motawa and Almarshad (2013) proposed an integrated knowledge-based BIM system to capture information and knowledge with the purpose of perceiving the extent to which a building is deteriorating, thus to carry out preventive or corrective measures. A corresponding system developed by Ho et al. (2013) indicated that the BIM-based knowledge sharing management (BIMKSM) system could be an effective process of promoting knowledge sharing among construction practitioners. A study performed by Josephson and Hammarlund (1999) suggested that the lack of knowledge, information, and motivation were generally considered to be the primary factors inducing the occurrence of defects due to design errors in building construction projects. Results showed that a total of 62% of design defects could be ascribed to the inadequacy of knowledge and information.

4.3 Impacts of BIM Implementation on Construction Productivity during Construction Stage

4.3.1 Introduction

Although the usage of BIM for improving construction productivity has attracted much attention of researchers, little research has been reported on quantifying the comprehensive impacts of BIM implementation on construction productivity in construction stage. For example, Issa and Suermann (2009) conducted a survey assessing the impact of BIM implementation on construction process based on six primary construction key performance indicators commonly used in the construction industry: quality control (rework), on-time completion, cost, safety, dollar/unit performed, and units per man hour. Results showed that quality, on-time completion, and units per man hour were the highest ranking KPIs responses preferred when utilizing BIM. Case studies conducted by Chelson (2010) demonstrated that field productivity gains could be improved as high as 5 to 40% according to BIM practices. Bryde et al. (2013) investigated 35 construction projects that adopted BIM and identified the most reported benefits of BIM implementation were cost savings and containments, together with reduced project schedules. Generally, when a building is constructed in a BIM-based virtual environment, productivity gains can be achieved through better collaboration and coordination among AEC professionals, diminished production cycle times, reduced project costs with faster cost estimation, and improved quality performance (Eastman et al., 2011; Bryde et al., 2013).

4.3.2 BIM-based Construction Productivity Gains

4.3.2.1 Labor Productivity (LP)

The positive impacts of BIM on labor productivity had been investigated and demonstrated by many scholars. Four detailed case studies that utilized BIM were analyzed by Kaner et al. (2008), revealing certain amelioration in design quality due to error-free drawings, and a stable growing enhancement in labor productivity. Khanzode et al. (2008) investigated a case study quantitatively measuring the benefits of BIM on labor productivity. Findings showed that labor productivity of all the MEP contractors could be improved ranging from 20%-30% through BIM-enabled coordination of MEP systems. Poirier et al. (2015) conducted an action research which aimed at assessing and quantifying the impacts of BIM on project performance in terms of labor productivity based on a large commercial project. Results indicated an apparent increase in labor productivity, and a substantial improvement ranging from 75% to 240% when combined with BIM and prefabrication. Furthermore, this research initiated an idea allowing organizations to incessantly evaluate the project performance in the light of labor productivity.

4.3.2.2 Communication and Coordination (CC)

Ho et al. (2013) developed a visual BIM-based knowledge sharing platform allowing project professionals to communicate and reused information easily and effectively, thus to reduce the time and cost for addressing construction problems. As indicated by Nath et al. (2015), significant productivity improvement opportunities could be obtained by BIM-enabled tool for enhancing communication and collaboration among all project participants. Improved collaboration would greatly enhance the flexibility and clarity among all project stakeholders with the aim of facilitating construction process. In addition, the proactive involvement of all practitioners could streamline the integrated information sharing process to discover and address problems in a timely manner (Kim et al., 2015).

4.3.2.3 Site Resource Planning and Management (SRPM)

BIM has been utilized for Augmented Reality (AR) to enhance the productivity of on-site work. Likewise, a workspace conflict verification system was developed by Moon et al. (2014) to analyze the workspace information by integrating algorithms that include the automated generation of workspace models and an automatic check of workspace conflict based on BIM simulation. This practical system can reduce workspace conflicts to improve productivity, and overlapped activities can be rescheduled to minimize the collisions. Additionally, by using BIM models, construction professionals can figure out and optimize the labor force along with required materials and equipment during construction. Combined with construction schedules, accurate quantities of materials and equipment can be evaluated by BIM model with the purpose of offering sufficient resource at different points in time, as well as decrease wastage (Chau et al., 2004; Becerik-Gerber et al., 2011; Kim et al., 2015).

4.3.2.4 Simulate master schedules and construction sequences (SSS)

With a 3D BIM model, it is available to virtualize constructability and construction sequences of projects before commencement (Grilo and Jardim-Goncalves, 2010), thus to predict potential collisions and construct a reasonable construction schedule with rational construction sequences. For example, a building information model can be effectively applied to coordinate material distribution and optimize delivery schedules for all building components and construction processes. BIM software makes the quantities of building components automatically inserted, extracted or updated when any modifications made within the model, resulting in approximately 80% reduction of time for cost estimation (Azhar, 2011). Wang et al. (2014a) proposed an interface system that deployed the BIM’s ability with respect to quantity takeoffs of required materials to support site schedules and sequences simulation, coordinate multiple operational sequences, and estimate resource allocation schemes, ultimately leading to the generation of better project schedule. This can serve as a base to precisely arrange time duration and allocation strategies of work tasks in order to create a reasonable and optimal construction schedule. It should be noted that BIM-based decision support method for master planning could be primarily applied in design and construction stage.

Therefore, Kim et al. (2015) developed an integrated decision support systems allowing automatically assessment and visualization of multiple development scenarios to assist stakeholders in making informed decisions for the master plans over time.

4.3.2.5 Shorten Project Duration (SPD)

Time savings has been regarded as the most beneficial factors that utilizes BIM for productivity improvement during construction. A study performed by Bryde et al. (2013) showed that significant time savings were obtained by the implementation of BIM during design and construction process, leading to improved coordination and communication of all practitioners. Enhanced collaboration among different practitioners could facilitate the decision-making process, and reduce rework due to better production quality with the aim of reaching duration improvement (Azhar, 2011; Issa and Suermann, 2009). In addition, drawings from different professions can be imported to BIM software to conduct clash detection, thus to save time and reduce repeated work. This can lead up to 7% reduction in project duration (CRC, 2007). Nath et al. (2015) proposed a BIM-based workflow in an attempt to streamline the shop drawings generation process, suggesting that total productivity could be improved by nearly 38% for the whole time. This could substantially reduce the error-prone manual manipulation of extracting building components information into actual construction process (Kim and Cho, 2015).

4.3.2.6 Quantity Takeoff and Cost Estimation (QTCE)

Conventional ways of cost estimates have difficulties to accommodate cost overruns incurred by unexpected omissions or errors, unforeseen situation, like delay and rework (Mills et al., 1999). Due to the complex consumption and disbursement of funds and limited technologies to instantly update the enormous amount of information, it is hard for stakeholders to manage and control detailed cost, coping with data in real time (Li et al., 2014a). Numerous previous studies have demonstrated that BIM is a prominent approach of addressing costs problems by optimizing construction design, construction schedule, and resource management, reducing rework and minimizing unnecessary errors and waste (Singh et al., 2011; Li et al., 2014a).

Based on the quantitative information in the BIM, construction cost estimation can be produced by linking it to a cost database. Any detailed information or changes made to the project will be reflected in the model (Grilo and Jardim-Goncalves, 2010). Shen and Issa (2010) demonstrated that BIM-assisted Detailed Estimating (BADE) tools have advantages of traditional estimating methods for entry-level users. The performance of detailed estimate was considerably affected by both the visualization and aggregation functions of BADE tool. Wang et al. (2013a) proposed a framework and explored that BIM can be beneficial to facility management in the design phase, where early adoption of BIM can dramatically reduce life-cycle costs. As figured out by Li et al. (2014a), BIM-base cost estimates can largely alleviate the workloads of estimators and reduce the likelihood of loss and errors. They also proposed a cost-oriented framework in order to prove the merits of BIM. Azhar (2011) also pointed out that BIM-based approach can achieve nearly 40% reduction of unbudgeted change and 3% improved precision of cost estimation.

4.3.2.7 Minimize Project Costs (MPC)

Potential productivity improvements can also be found in minimizing project costs. Giel and Issa (2011) carried out case studies concentrated on return on the investment (ROI) of implementing BIM based on three similar projects. Findings implied that BIM was a desirable and valuable investment, as it could be beneficial for cost savings associated with less rework, reduced requests for information (RFIs), fewer change orders, and shortened project duration. BIM allows clash detection and in the early design stage, thus to avoid rework and change orders in the construction stage. While applying BIM technology, conflicts or design deficiencies can be identified before actual construction, hence, the cost of rework can be substantially decreased (Barlish and Sullivan, 2012). As identified by Bryde et al. (2013), significant cost savings could be achieved by effectively implementing BIM on construction projects due to the enhanced collaborative environment within less rework and fewer change orders.

4.3.3 A Conceptual Framework

Based on the aforementioned factors, a conceptual model was developed to evaluate the impacts of BIM on construction productivity, as shown in Figure 3.2.

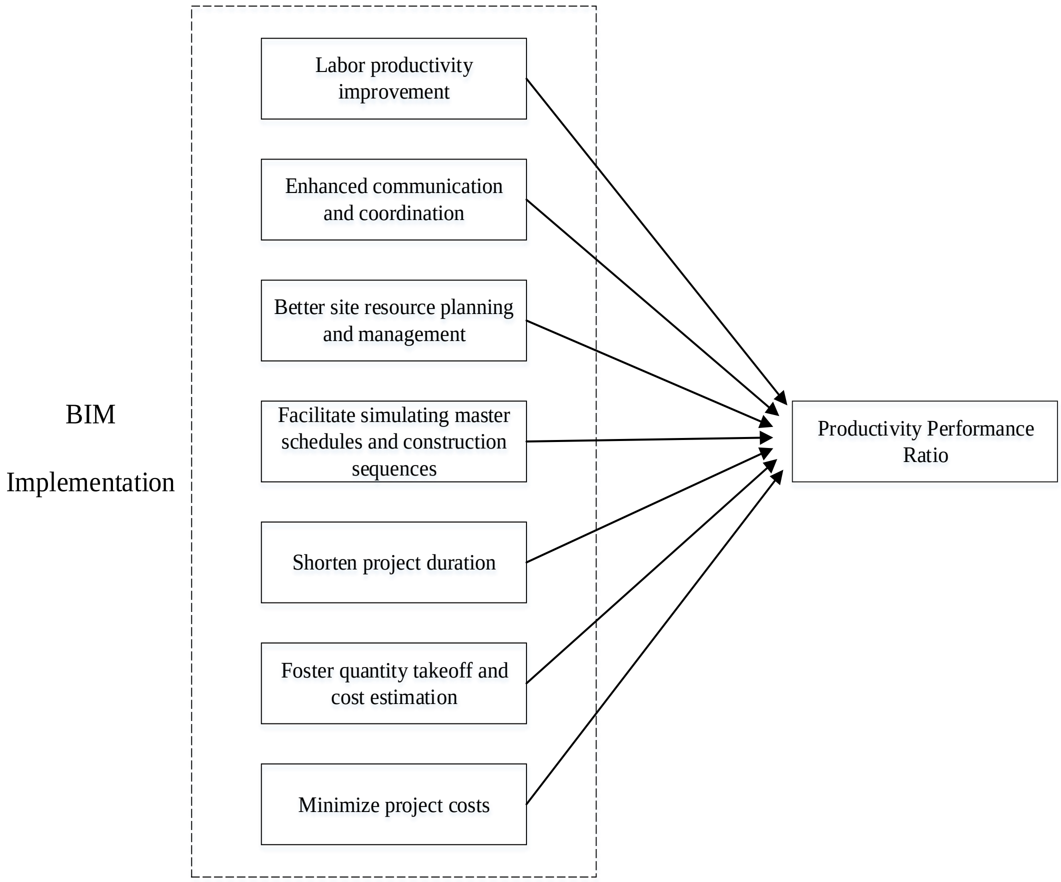


Figure 4.2 Conceptual framework of BIM-enabled construction productivity gains model

4.4 Chapter Summary

This chapter first expresses the desirability of reducing design error in the construction projects, then research on the impacts of BIM implementation in reducing design error during design stage are examined to establish a conceptual framework of design error reduction model. By reviewing relevant research with respect to the impacts of BIM on construction productivity, a conceptual framework of BIM-enabled construction productivity gains model is also built up.

CHAPTER 5 THE IMPACTS OF BIM IMPLEMENTATION IN REDUCING DESIGN ERROR

5.1 Introduction

This Chapter aims to assess the impacts of BIM implementation in reducing design error, validate the conceptual model based on the different design error reduction (DER) indicators, as established in Chapter 4, incorporating clash detection (CD), design coordination (DC), human error (HE), drawing error (DE), teamwork and cooperation (TC), constructability and practicality (CP), and knowledge and information sharing (KI), and identify which indicator can yield the better ability to predict the effects of BIM implementation in reducing design error. Seven underlying attributable indicators identified from the literature are discussed in section 5.2. Section 5.3 describes measurement development and the methods of data collection. Data analysis and results are presented and discussed in section 5.4. These outcomes are further analyzed in section 5.5. Section 5.6 summarizes the chapter.

5.2 Methods of Data Collection

5.2.1 Measurement Development

With the purpose of identifying the impacts of BIM in reducing design error, a questionnaire survey was conducted as the primary means of collecting project-based data. Generally, a questionnaire survey is applied to collect quantitative data scaled by respondents, and thus for statistical analysis. The strength of utilizing questionnaire survey is to acquire a large amount of quantitative data, providing sources of investigating and synthesizing the major findings (Creswell, 2013). As suggested by Bradburn et al. (1992), the mixed data collection methods, consisting of literature review and semi-structured interviews, were employed in order to better design the survey and to acquire more accurate, valid, and detailed information with respect to the respondents. In achieving this, an exploratory and thorough literature review was initially performed to gain a rudimentary understanding of the attributable factors affecting design errors through the implementation of BIM. Drawn on the information gleaned from the literature, a draft of the questionnaire survey was created in plain and clear language to strengthen the respondents' ability to make a sound judgment (Aibinu and Jagboro, 2002), in order to collect data regarding BIM-related factors influencing design error. Then, with the purpose of yielding a balanced review of the research topic from different backgrounds, the questionnaire was sent to 14 experts in the field of BIM implementation, incorporating two academic researchers, three clients, three designers, three contractors, and three consultants. The aim of this pre-test process was to evaluate the appropriateness and rationality of the questionnaire, examine the scope and content, as well as identify the obscure expressions (Oppenheim, 2000). Based on the feedback from experts, the questionnaire was further modified and subsequently disseminate to targeted project-based respondents.

The questionnaire items applied to measure the impacts of BIM in reducing design errors were developed built on the information captured from the literature and experts' views. These factors were principally based on a comprehensive review of the frameworks presented by Eastman et al. (2011), Rajendran et al. (2013), Azhar (2011), Azhar et al. (2012), Lee et al. (2015) and Love et al. (2011c) as well as the outcomes of preliminary expert interviews. With the additional modification based on the feedback, a total of 7 factors were ultimately encompassed into the questionnaire (see Table 5.1). The overall impact of BIM implementation in reducing design error was evaluated on a five-point scale. Then, respondents were asked to rate the level of agreement on the importance of each separate items based on a five-point Likert scale (**1** indicates "**strongly disagree**" and **5** indicates "**strongly agree**"), and their detailed measurement items are presented in Table 5.1.

Table 5.1 Measurement items for analyzing the impacts of BIM in reducing design error

Code	Items	Reference
CD	Clash detection	Eastman et al. (2011); Azhar (2011); Eastman et al. (2008); Eastman et al. (2011)
DC	Design coordination	Wang et al. (2013b); Eastman et al. (2011)
HE	Human error	Lee et al. (2015); Love et al. (2011b); Love et al. (2011a); (Love et al., 2011c)
DE	Drawing error	Azhar (2011); Kaner et al. (2008); Sacks (2004); Sacks and Barak (2008); Bernstein et al. (2012); Eastman et al. (2011); Rajendran et al. (2013)
TC	Teamwork and cooperation	Azhar et al. (2012); Aranda-Mena et al. (2009); Rajendran et al. (2013); Baoping et al. (2010); Wu and Issa (2013)
CP	Constructability and practicality	Sacks et al. (2010b); Rajendran et al. (2013); Bynum et al. (2013); Azhar (2011)
KI	Knowledge and information sharing	Linderoth et al. (2014); Benjaoran and Bhokha (2009); Ho et al. (2013); Motawa and Almarshad (2013); Josephson and Hammarlund (1999)

Note: Where CD = clash detection, DC = design coordination, HE = human error, DE = drawing error, TC = teamwork and cooperation, CP = constructability and practicability, KI = knowledge and information sharing.

5.2.2 Sampling and Data Collection

This study only incorporated experts and construction projects from the Chinese mainland to construct the sampling frame. Since the implementation of BIM was relatively rare in China, a completely random sampling or stratified sample would not be appropriate. Alternatively, diversified sorts of BIM-based construction projects and proper respondents were selected and identified by contacting professionals in BIM implementation, visiting pioneering corporations skilled in adopting BIM, searching technical groups of developing BIM technology. The target respondents were identified by selecting the informed senior and specialized personnel directly participating in BIM-based projects. Consequently, a wide variety of BIM-based projects with five developed geographic locations, together with different project characteristics was selected to intensify the representativeness of the sample and thus yield a better view of industry practice.

The finalized questionnaire involves two parts. The first part was designed to collect background information regarding the respondents and projects, such as work experience, educational background, type of project participants, the number of BIM-based projects involved in, and so forth. The second part contains rating the overall impact of BIM implementation in reducing design error and the seven contributory factors. The data of questionnaire survey was collected by using three means including e-mail invitation, online survey system (www.sojump.com) and personal visits. Over a period of 3 months from November 2015 to January 2016, ultimately, a total of 155 questionnaires were returned from four regions with five cities of China, including North (Beijing), South (Guangzhou and Shenzhen), East (Shanghai), West (Chongqing). After excluding invalid or incomplete questionnaires, the remaining 120 valid questionnaires, representing a great response rate of 77.4%, were identified and used for subsequent analysis. After completing the questionnaires, most respondents were glad to provide further explanations of their answers and expected to obtain the results of the questionnaires. Among the 120 valid responses, 46.67% were collected through the online survey system, with the remaining 35% and 18.33% gleaned by personal visits and e-mail invitation, respectively. ANOVA and Chi-square test were employed to compare the answers from the three types of responses, and no significant differences were found. The demographic information of these 120 respondents is presented in Table 5.2.

Table 5.2 Demographic information of targeted respondents

Parameter	Category	N	%	Parameter	Category	N	%
type of project participants	Client	25	20.83	Number[a]	1-2	83	69.17
	Designer	32	26.67		3-4	25	20.83
	Contractor	35	29.17		5-6	8	6.67
	Consultant	28	23.33		Above 6	4	3.33
Work experience	Below 2	22	18.33	Number[b]	Below 1	8	6.67
	2-5	39	32.50		1-3	67	55.83
	5-10	42	35.00		3-5	30	25.00
	10-15	12	10.00		5-7	10	8.33
	Above 15	5	4.17		Above 7	5	4.17
Educational background	Below junior college	5	4.17				
	Junior college	9	7.50				
	Bachelor	65	54.17				
	Master	33	27.50				
	Doctor	8	6.67				

[a]Number of BIM-based projects involved; [b]Number of years for implementing BIM.

The respondents come from a mixed type of project participants, with 20.83% from clients, 26.67% from designers, 29.17% from general contractors, and 23.33% from consultants. Most of the respondents are senior and professional personnel knowledgeable of BIM implementation or directly involved in the BIM-based projects. 49.17% of the respondents showed more than 5 years' work experience. In addition, 88.34% hold Bachelor's degree or higher degree. These are perceived sufficient to acquire sound judgement from qualified respondents in this research. However, 69.17% of the respondents only participated in one or two BIM-based projects. In consistent with this results, 62.50% of the respondents showed that years of implementing BIM were still stayed on the preliminary stage (below 3 years). The results indicated that the implementation of BIM in Chinese construction projects was still in an infant and immature stage.

Table 5.3 Demographic information of targeted projects

Parameter	Category	N	%
Project size	Below 100 million	22	18.33
	100-500 million	30	25.00
	500-1000 million	26	21.67
	1000-1500 million	18	15.00
	1500-2000 million	13	10.83
	Above 2000 million	11	9.17
Location	North China	28	23.33
	East China	56	46.67
	South China	24	20.00
	West China	12	10.00

As shown in Table 5.3, the projects are diverse in terms of project size and location. The majority (86.67%) of BIM-based projects are mainly located in the regions of East China, North China, and South China, suggesting a non-balanced distribution of surveyed projects. This unsymmetrical distribution was principally attributed to the imbalanced level of economic development, especially located in the large cities, such as Shanghai, Beijing, Guangzhou and Shenzhen. The distribution of investment value of the projects was primarily placed on the spectrum ranging from 100 to 1000 million, with a total percentage of 46.67%.

5.3 Data Analyses and Results

5.3.1 Descriptive Statistics and Analysis of Variance

Descriptive statistics analysis of responses derived from targeted respondents is presented in Table 5.4, showing the mean score with the standard deviation of each indicator. The bold value in Table 5.4 denotes the ranking of importance ratings for each indicator. As demonstrated by Fraenkel et al. (1993), in case of two or more indicators processing the same mean value, the one with lower standard deviation would be deemed as more influential. Therefore, the ranking of KI is much higher than that of TC with the same mean value. Of all the seven indicators, Clash detection and design coordination obtain the highest mean score with a value of 4.41 and 4.29, respectively. These are followed by drawing error (4.17), constructability and practicability (4.03), and human error (3.92). Knowledge and information sharing, and teamwork and cooperation are the two least scored indicators.

Table 5.4 Measurement indicators for constructs in assessment of reducing design error

Construct	Code	Items description	Mean	SD
Clash detection	CD	Early detection of collisions via BIM substantially reduced design error and subsequent rework	4.41(**1**)	0.66
Design coordination	DC	Integrating and coordinating all the design systems with the goal of avoiding conflicts and enhancing collaboration	4.29(**2**)	0.76
Human error	HE	Human error could be reduced through the implementation of BIM	3.92(**5**)	0.87
Drawing error	DE	Drawing errors/omissions could be greatly ameliorated through BIM implementation	4.17(**3**)	0.78
Teamwork and cooperation	TC	BIM could enhance TC in the early design phase with the purpose of enhancing communication and facilitate design process	3.88(**7**)	0.90

Constructability and practicality	CP	BIM could substantially improve the efficiency and effectiveness of delivery processes and the constructability of a facility	4.03(**4**)	0.83
Knowledge and information sharing	KI	KI could be sufficiently interchanged and applied among construction practitioners, thus to discover and alleviate problems in the early design phase	3.88(**6**)	0.83

The aggregated impacts of BIM on design error reduction (DER) was also measured by the same respondents via the five-scale method. Results showed a mean value of 4.03 with the standard deviation 0.81. This aggregated factor was used to as the dependent variable for later regression analysis. Reliability of the constructs was tested by deploying Cronbach's coefficient alpha. The alpha levels for each of the constructs were higher than the threshold of 0.70, indicating the scales were a reliable measure to be accepted (Cronbach, 1951). A test for internal consistency and reliability of these indicators provided a satisfactory Cronbach's coefficient alpha of 0.874. ANOVA tests were then performed to identify how the aggregated impacts of BIM on DER were associated with different types of project participants, respondents' work experience, and project size. The results of these tests are illustrated in Table 5.5 and Table 5.6.

Table 5.5 Results of ANOVA tests for the aggregate impacts of BIM on DER by respondent's background

Parameter	Category	N	Mean	SD		SS[a]	F-value	p-value
type of project participants	Client	25	3.96	0.83	Between groups	0.57	0.29	0.831
	Designer	32	4.16	0.86	Within groups	76.09		
	Contractor	35	3.84	0.65	Total	76.66		
	Consultant	28	4.09	0.96				
Work experience	Below 2	22	3.76	0.74	Between groups	3.64	1.43	0.232
	2-5	39	4.02	0.82	Within groups	73.03		

5-10	42	4.18	0.79	Total	76.67
10-15	12	3.96	0.86		
Above 15	5	3.92	0.71		

[a]SS= sum of squares

As displayed in Table 5.5, designers report the highest rating than any other type of project participants. And the type of project participants is found to be insignificantly associated with the dependent variable, indicating that the impacts of BIM on DER have no significant correlation with the type of project participants. A similar result is also revealed in the association between respondents' work experience and the impacts of BIM on DER. Both of the results are further analyzed by the ordinary least squares (OLS) regression method, which indicates the same insignificant outcomes. Although no statistically significant differences are evidenced by ANOVA test between the impacts of BIM on DER and project size, as shown in Table 5.6, the result of OLS regression analysis demonstrates the two variables are statistically positively associated ($F= 8.059$, $p= 0.005$, $B= 0.131$). This result suggests that larger projects may have greater impacts on design error reduction through BIM implementation. A series of ANOVA tests are also conducted to assess the differences in the mean value of seven independent variables (including CD, DC, HE, DE, TC, CP, KI) from different backgrounds. The comparison results reveal that none of the difference is significant at the level of 5% confidence interval (p-values range from 0.156 to 0.760), indicating that both the types of project participants and work experience have not aroused substantial data biases.

Table 5.6 Results of ANOVA tests for the aggregate impacts of BIM on DER by project background

Parameter	Category	N	%	Mean	SD		SS[a]	F-value	p-value
Project size	Below 100 million	22	18.33	4.18	0.85	Between groups	5.87	1.89	0.121
	100-500 million	30	25.00	3.97	0.77	Within groups	70.80		
	500-1000 million	26	21.67	4.17	0.65	Total	76.67		
	1000-1500 million	18	15.00	3.76	0.78				
	1500-2000 million	13	10.83	3.89	0.75				
	Above 2000 million	11	9.17	3.85	1.04				

[a]SS= sum of squares

5.3.2 Multiple Regression Analysis

In identifying the impacts of seven potential influential indicators on design error reduction, multiple regression analysis was performed by using SPSS (Version 20) with the data from 120 respondents. Multiple regression analysis is employed to investigate the relationship between a single dependent variable (DER) and several potential independent variables, including clash detection (CD), design coordination (DC), human error (HE), drawing error (DE), teamwork and cooperation (TC), constructability and practicality (CP), knowledge and information sharing (KI). An assessment of internal consistency and reliability of these indicators provides a satisfactory Cronbach’s coefficient alpha of 0.874. Multicollinearity is tested by the variance inflation factors (VIF), a measure that evaluates the degree of multicollinearity among the predictive variables (O’brien, 2007). Most commonly used the rule of thumb associated with VIF is 10, indicating a sign of severe collinearity among potential independent variables (Draper and Smith, 2014). Standardization of the coefficient is habitually employed to address the problems that which of the predictable variables have a greater effect on the dependent variable regardless of the different units measured in the multiple regression model (Aiken et al., 1991). Regression diagnostics was undertaken to examine the appropriateness of the assumptions made by fitting a regression model to a specific set of data (Belsley et al., 2005). With the utilization of SPSS 20.0, it is found that the regression model is generally fitted under the following assumptions of linearity (the relationships between the DER and the predictive variable is linear), normality (the errors is normally distributed), homoscedasticity (the errors variance is constant), and independence (the errors associated with one observation are not correlated with the errors of any other observation).

The resultant outcomes of regression analysis on the single dependent variable DER and the independent variables are depicted in Table 5.7. The maximum VIF (2.368) in the Table was greatly lower than the threshold point of 10, implying that multicollinearity would not increase the standard errors of the DER model estimate (VIF ranging from 1.748 to 2.369). Multiple regression equations (RPE) with six determining factors are finally reflected as Equation 5.1. The outcomes from the best-fit evaluation of multiple regression model indicated a p-value of less than 0.05 with its associated adjusted R^2 values more than 0.70, which implied goodness-of-fit models. Results of the multiple regression analysis revealed the value of adjusted R^2 was 0.752, indicating a good fit model. The Durbin-Watson value was 2.094, which meant the residual errors was also normally distributed.

Table 5.7 Multiple regression analysis for DER model

Model	Design error reduction model					
Independent variable	Unstandardized coefficients		Standardized coefficients	t	p	Multicollinearity
	B	Standard error	β			VIF
Constant	0.255	0.276				
CD	0.506***	0.600	0.433	1.759	0.001	1.866

DC	0.245*	0.074	0.216	2.225	0.028	2.368
HE	-0.022	0.063	-0.021	-0.346	0.230	1.748
DE	0.255***	0.064	0.239	3.813	0.000	1.883
TC	0.049*	0.062	0.021	0.256	0.032	2.186
CP	0.236**	0.060	0.203	1.759	0.002	1.866
KI	0.122*	0.063	0.105	1.936	0.026	2.019

Note: Where clash detection = CD, design coordination = DC, human error = HE, drawing error = DE, teamwork and cooperation = TC, constructability and practicality = CP, knowledge and information sharing = KI; P* < 0.05, P** < 0.01, P*** < 0.001

As shown in Table 5.7, all the six independent variables (CD, DC, DE, TC, CP, and KI) are statistically significant with the dependent variable DER, except for HE. The p-value of this independent variable indicates that human error is not significantly associated with DER at the 5% level of the confidence interval. Consequently, the regression analysis determined six significant independent variables, which are positively associated with the dependent variable DER. These are:

*CD***: Early detection of collisions via BIM substantially reduced design error and subsequent rework.*

DC: Integrating and coordinating all the design systems with the goal of avoiding conflicts and enhancing collaboration.*

*DE***: Drawing errors/omissions could be greatly ameliorated through BIM implementation.*

TC: BIM could enhance teamwork in the early design phase with the purpose of enhancing communication and facilitate the design process.*

*CP**: BIM could substantially improve the efficiency and effectiveness of delivery processes and the constructability of a facility.*

KI: Knowledge and information could be sufficiently interchanged and applied among construction practitioners, thus to discover and alleviate problems in the early design phase.*

Drawn on the six determining indicators, the design error reduction model was modified (and the associated valences of the standardized β weights) to demonstrate the causal relationship between the dependent and independent variables, as shown in Figure 5.1. Final model coefficients are presented in Table 5.7. The regression equation can be expressed as:

DER Model = 0.255 + 0.506CD + 0.245DC + 0.255DE + 0.049TC + 0.236CP + 0.122KI   Eq. (5.1)

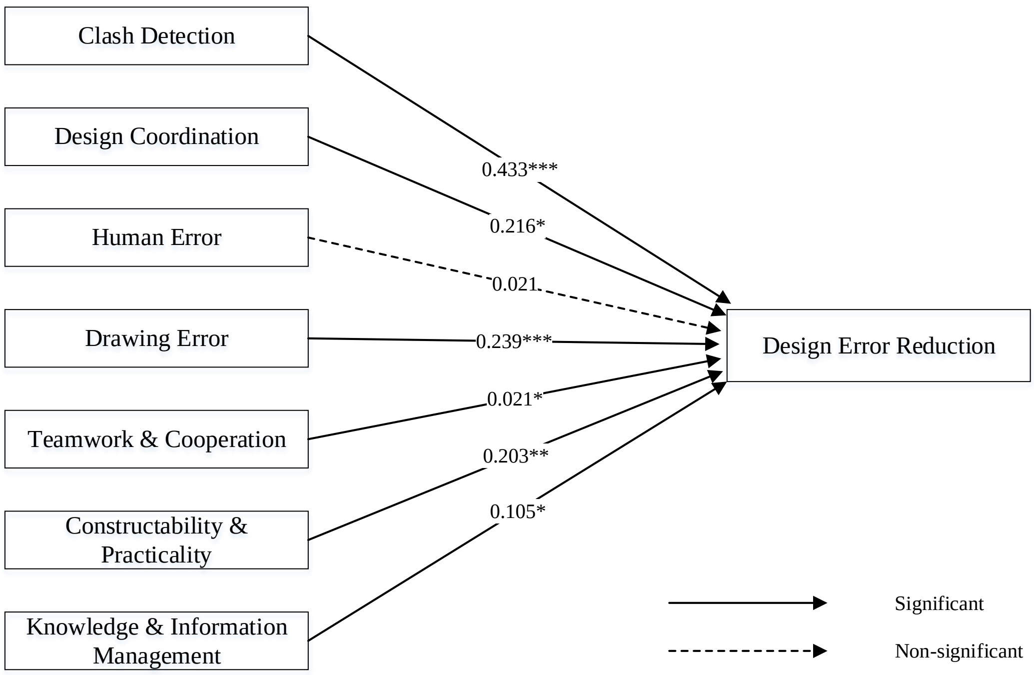


Figure 5.1 Results of multiple regression analysis for design error reduction model

5.4 Discussion of Findings

The primary research objective of this chapter is to identify the impacts of BIM in reducing design error in Mainland China, a country with the largest construction industry of the world. Literature review is employed to conduct an overview of the implementation of BIM in reducing design error in Chinese mainland construction projects, thus to establish a conceptual framework to measure how the contributory indicators affecting design error through the implementation of BIM. Then, data derived from questionnaire survey is used to examine the conceptual model with the purpose of developing a validated and modified model based on the practices of construction practitioners.

Seven potential indicators are found to be influential factors affecting design error from literature, which comprise clash detection (CD), design coordination (DC), human error (HE), drawing or document errors/omissions (DE), teamwork and cooperation (TC), constructability and practicality (CP), and knowledge and information management (KI). Clash detection and design coordination are found to be the two-most important (Mean = 4.41, 4.29 respectively) indicators from respondents' rating. This corresponds with the previous investigations that BIM was frequently used as a visualization tool allowing for automatic detection of errors related to building components (Lee et al., 2012; Lee et al., 2015; Love et al., 2011c).

Then, multiple regression analysis (ordinary least square) is deployed to inspect and verify the latent indicators. Ultimately, six determining indicators are identified. As shown in Fig. 5.2, six attributable factors are revealed to be statistically significant with the impacts of BIM on design error reduction, among which clash detection (standardized $\beta = 0.433$, $p^{***} < 0.001$) has the best ability to positively affect design error reduction. Thus, clash detection is perceived as the most beneficial factor from the implementation of BIM in deducting design error. After CD, DE (standardized β = 0.239, $p^{***} < 0.001$), DC (standardized $\beta = 0.216$, $p^{***} < 0.05$), and CP (standardized $\beta = 0.433$, $p^{**} < 0.01$) are also found to have great potential impacts on design error reduction. KI (standardized $\beta = 0.105$), $p^* < 0.05$) and TC (standardized $\beta = 0.021$, $p^* < 0.05$) are the two least influential factors affecting design error. Noteworthy, the indicator of human error is excluded from the model by conducting multiple regression analysis using ordinary least square method. Results showed that human error is no statistically significant associated with the dependent variable DER. This outcome is in consistent with the Reason (2000) and Love et al. (2011c)'s belief that human error is an innate feature of human nature. Also, Foord and Gulland (2006) ascertained that it is impossible to design technological systems to preclude human errors. Additionally, the assertion that BIM will reduce human errors during design stage is misguided, with respect to the diverse sets of exogenous and endogenous variables affecting a designer's cognition and capability to execute tasks (Busby, 1999; Love et al., 2011a).

The research findings provide several practical implications. BIM users need to boost their professions to facilitate the design process and to proficiently plan and manage the design and documentation process with the aim of intensifying the effectiveness of clash detection, design coordination, and drawing error containment. In addition, the teamwork of all construction practitioners engaged in the design process should be improved to reach close cooperation and collaboration through the extensive utilization of BIM. Moreover, designers should enhance the constructability and practicality of design work through effectively facilitating knowledge and information sharing process both within different design teams and among all stakeholders. Despite of these implications from empirical study, as indicated by Love et al. (2011c), BIM will considerably improve the efficiency and effectiveness of design process only by juxtaposing with other organizational and project-related strategies that have been verified. Otherwise, BIM will become a sole driver for error containment, which may give rise to the failures that would impair the performance and productivity of construction projects. The effective implementation of BIM in design stage can be a source of improving productivity for subsequent stages, such as construction and operation (Son et al., 2015).

5.5 Chapter Summary

Design error is not only a recognized hazard for cost and schedule overruns in Chinese construction projects, but a global plague in the construction industry. Findings from this chapter consolidate the existent knowledge with recent new evidence from Mainland China projects, which aids to expand the existing intellectual cognition with respect to construction community by construction practitioners. Assessing the effects of BIM implementation on design error reduction are vitally important for promoting industry practice. Based on an investigation of 120 respondents from BIM-based construction projects, this chapter has developed a design error reduction (DER) model to measure the impacts of BIM implementation in reducing design error. Finally, six determining factors are identified.

CHAPTER 6 THE IMPACTS OF BIM IMPLEMENTATION ON CONSTRUCTION PRODUCTIVITY

6.1 Introduction

Relied on the investigation of 120 professionals from BIM-based construction projects, Chapter 5 has empirically examined how and to what extent the impacts of BIM implementation on design error reduction during the design stage. Although building up a design error reduction model and proffering insightful thoughts into the association between BIM implementation and design error reduction, the positivistic research in Chapter 5 has not comprehensively investigated the impacts of BIM on construction projects during the construction stage. As illustrated in Chapter 2, the large majority of prior studies have primarily concentrated on identifying incentive factors and barriers of BIM adoption in the construction industry (Bernstein and Pittman, 2004; Cerovsek, 2011a; Ku and Taiebat, 2011; Gu and London, 2010), or on unfolding project benefits gained from BIM utilization in construction projects (Bryde et al., 2013; Poirier et al., 2015; Hergunsel, 2011; Barlish and Sullivan, 2012), or on reporting the business value or potential profitability of applying BIM (Bernstein, 2015; Bernstein et al., 2012; Young et al., 2009; Lee et al., 2012). Nevertheless, despite of some research having measuring the impacts of BIM on labor productivity at activity level (Poirier et al., 2015; Kim et al., 2015), sparse scholarly attention has been focused on demonstrating the principal impacts of BIM implementation on construction productivity at project level during the construction stage.

Therefore, drawn on the conceptual framework concerning the impacts of BIM implementation on construction productivity, as developed in Chapter 4, this chapter aims to test the conceptual model for probing deeper into how and to what extent the contributory factors can influence the project-level construction productivity. As illustrated in Chapter 4, the variables of labor productivity (LP), communication and coordination (CC), site resource planning and management (SRPM), SSS (simulate master schedule and construction sequences), shorten project duration (SPD), quantity takeoff and cost estimation (QTCE), and minimize project cost (MPC) are perceived as reflective factors on BIM-enabled construction productivity gains. Additionally, productivity performance ratio is utilized to measure the aggregate impact of BIM implementation on construction productivity.

6.2 Methods of Data Collection

6.2.1 Measurement Development

With the aim of empirically testing the conceptual framework proposed in Section 3.3, the questionnaire survey was utilized as the primary means to collect data from BIM-based construction projects. The advantage of using questionnaire survey is to have a large amount of quantitative data, allowing exploring and synthesizing the major findings (Creswell, 2013). Eisenhardt (1989) suggested that mixed data collection methods, comprised of document analysis and semi-structured interviews, were deployed to better conceive the questionnaire survey and to obtain more accurate, specialized, and elaborate information from the target respondents. In achieving this, an exploratory and exhaustive document analysis was first performed to gain a preliminary understanding of the influential indicators affecting construction productivity through the implementation of BIM. Based on the information gleaned from the literature and industry practice, a draft of the questionnaire survey was formulated in plain and clear language to reinforce the respondents' ability to make a sound judgment (Aibinu and Jagboro, 2002). Semi-structured interviews with ten experts were then carried out to pre-test the rationality and validation of related constructs. The ten interviewed professions with different backgrounds incorporated two academic researchers, two owners/clients, two designers, two general contractors, and two consultants. All these professionals have specialized knowledge of BIM implementation and experienced industry practices. Based on the comments from these professionals, some vague expressions regarding measurement items were further revised and subsequently distribute to targeted project-based respondents.

The modified questionnaire associated with the analysis in this chapter was structured into two parts. The first part attains general information such as the type of project participants, year of implementing BIM, project size, and so forth. The second part was designed to evaluate and measure the extent of attributable factors on construction productivity in the surveyed project, and assess the BIM-enabled productivity gains. Finally, a total of eight variables have been measured in the questionnaire survey: productivity performance ratio (PPR), labor productivity (LP), communication and coordination (CC), site resource planning and management (SRPM), simulate master schedules and construction sequences (SSS), shorten project duration (SPD), quantity takeoff and cost estimation (QTCE), minimize project cost (MPC). The variable of PPR was utilized to evaluate the aggregated impact of BIM implementation on project-level construction productivity, which was measured by the five-point scale items ("**1**" = **not at all influential**; "**5**" = **extremely influential**), and the variables of LP, CC, SRPM, SSS, SPD, QTCE, and MPC were all operationalized as reflective constructs based on five-point Likert scale (i.e. **1** represents "**strongly**

disagree" and **5** indicates "**strongly agree**"), and their detailed measurement items are presented in Table 6.1.

Table 6.1 Measurement items for constructs in analysis of the impacts of BIM implementation on construction productivity

Abbr.	Construct	Reference
LP	Labor productivity	Sacks and Barak (2008); Kaner et al. (2008); Khanzode et al. (2008); Poirier et al. (2015)
CC	Communication and coordination	Ho et al. (2013); Kim et al. (2015); Nath et al. (2015); Grilo and Jardim-Goncalves (2010); Gu and London (2010)
SRPM	Site resource planning and management	Chau et al. (2004); Wang et al. (2004); Becerik-Gerber et al. (2011); Kim et al. (2015)
SSS	Simulate master schedules and construction sequences	Moon et al. (2014); Azhar (2011); Kim et al. (2015); Wang et al. (2014a); Grilo and Jardim-Goncalves (2010)
SPD	Shorten project duration	Becerik-Gerber and Rice (2010); Azhar (2011); Nath et al. (2015); Kim and Cho (2015); Bryde et al. (2013); Issa and Suermann (2009)
QTCE	Quantity takeoff and cost estimation	Cheung et al. (2012); Azhar (2011); Singh et al. (2011); Mills et al. (1999); Grilo and Jardim-Goncalves (2010); Li et al. (2014a); Shen and Issa (2010);
MPC	Minimize project costs	Becerik-Gerber and Rice (2010); Azhar (2011); Giel and Issa (2011); Barlish and Sullivan (2012); Bryde et al. (2013)

Note: Abbr. = Abbreviation

6.2.2 Sampling and Data Collection

This investigation only incorporated professionals and construction projects from the Mainland China to construct the sampling frame. Since the implementation of BIM was relatively rare in China, a completely random sampling or stratified sample would not be appropriate. Alternatively, diversified sorts of BIM-based construction projects and proper respondents were selected and identified by contacting professionals in BIM implementation, visiting pioneering corporations skilled in adopting BIM, searching technical groups of developing BIM technology. The extent of data reliability is primarily determined by the data source and the background of corresponding personnel who filled out the questionnaire (Oppenheim, 2000). Thus, it was vitally important for respondents to have experiences and detailed knowledge regarding BIM implementation on construction projects. Therefore, the target respondents were identified by selecting knowledgeable senior and professional personnel directly involved in BIM-based construction projects. Consequently, a wide variety of BIM-based projects with five developed geographic locations, together with different types of well-informed project participants was selected to intensify the representativeness of the sample and thus yield a better view of industry practice.

The data of questionnaire survey was collected by using three means including personal visits, e-mail invitation, and online survey system (www.sojump.com). Over a period of 3 months from March 2016 to May 2016, ultimately, a total of 143 questionnaires were returned from four regions with five cities of China, including North (Beijing), South (Guangzhou and Shenzhen), East (Shanghai), West (Chongqing). After further omission of invalid or incomplete questionnaires, the remaining 102 valid questionnaires, representing a great response rate of 71.33%, were identified and used for subsequent analysis. Before filling out the survey, to avoid common method variance, the information of respondents and their answers were kept confidential. This procedural control means could assist in mitigating the potential response bias resulting from consistency motif and social desirability. After completing the questionnaires, most respondents were glad to provide further explanations of their answers and expected to obtain the results of the questionnaires. Among the 102 valid responses, 41.18% were collected by personal visits, with the remaining 33.33% and 25.49% gleaned by e-mail invitation and the online survey system, respectively. Analysis of variance and Chi-square test were employed to compare the answers from the three types of responses, and no significant differences were discovered. The demographic characteristics of the samples relating to the 102 valid responses are presented in Table 6.2 and Table 6.3.

Table 6.2 Demographic information of targeted projects

Parameter	Category	N	%
Project size	Below 100 million	17	16.67
	100-500 million	24	23.53
	500-1000 million	19	18.63
	1000-1500 million	19	18.63
	1500-2000 million	13	12.75
	Above 2000 million	10	9.80
Location	North China	26	25.49
	East China	42	41.18
	South China	27	26.47
	West China	7	6.86

As shown in Table 6.2, the surveyed projects are diverse in terms of project size and location in order to enlarge the representative of samples. The majority (93.14%) of BIM-based projects are mainly located in the regions of East China, North China, and South China, especially in the large cities, such as Shanghai, Beijing, Guangzhou and Shenzhen, indicating a possible non-balanced distribution of the surveyed projects. Such a non-balanced distribution could be principally attributed to the unbalanced level of economic development in China at present. The distribution of investment value of the projects was primarily placed on the spectrum ranging from 100 to 1500 million, with a total percentage of 60.78%. In order to properly examine whether the responses corresponding to the eight variables were affected by the project size, a chain of

ANOVA tests were performed to compare the differences in the mean values of the constructs, and no statistically significant association between project size and these measurement items (p-values of the ANOVA tests for PPR, LP, CC, SRPM, SSS, SPD, QTCE, MPC are 0.140, 0.182, 0.569, 0.772, 0.096, 0.567, 0.905, 0.753 respectively).

Table 6.3 Demographic information of targeted respondents

Parameter	Category	N	%	Parameter	Category	N	%
Type of project participants	Client	20	19.61	Number[a]	1-2	56	54.90
	Designer	20	19.61		3-4	31	30.39
	Contractor	38	37.25		5-6	11	10.78
	Consultant	24	23.53		Above 6	4	3.92
Work experience	Below 2	27	26.47	Number[b]	Below 1	16	15.69
	2-5	43	42.16		1-3	46	45.10
	5-10	22	21.57		3-5	30	29.41
	10-15	6	5.88		5-7	8	7.84
	Above 15	4	3.92		Above 7	2	1.96

[a]Number of BIM-based projects involved; [b]Number of years for implementing BIM.

The respondents come from a mixed type of project participants to further enlarge the diversity of targeted respondents, with 19.61% from clients/owners, 19.61% from designers, 37.25% from general contractors, and 23.53% from BIM consultants. Most of the respondents are senior and professional personnel knowledgeable of BIM implementation or directly involved in the BIM-based projects. 41.18% of the respondents had more than 5 years' work experience, and all of the respondents had the experience of implementing BIM or directly participating in BIM-based construction projects, indicating that samples are perceived sufficiently to acquire sound judgement from qualified respondents in this research. However, 54.90% of the respondents only participated in one or two BIM-based projects. Corresponding to this results, 60.78%

of the respondents showed that years of implementing BIM were still at the embryonic stage (less than 3 years). These results indicated that the implementation of BIM in Chinese construction projects was still in an infant and immature development stage.

6.3 Data Analyses and Results

6.3.1 Descriptive and Comparative Analyses

Descriptive statistics analysis of responses derived from targeted respondents is presented in Table 6.4, showing the mean score with a standard deviation of each variable. The variable of productivity performance ratio (PPR) was also measured by the same respondents via the five-scale method to assess the aggregated impacts of BIM on construction productivity. Results show a mean value of 4.08 with the standard deviation 0.67. This aggregated factor is used to as the dependent variable for later regression analysis. Of all the seven influential variables, SPD, SSS and CC obtain the relative highest mean score with a value of 4.40, 4.26, and 4.24, respectively, implying that these three variables were considered as the most influential factors affecting construction productivity through BIM implementation. The mean value of labor productivity (M= 4.01, SD= 0.64) and quantity takeoff and cost estimation (M= 4.07, SD= 0.57) are also at the relatively high level, suggesting that BIM-enabled labor productivity improvement and better cost estimation processes are also the prominent indicators influencing construction productivity. The mean score of SRPM and MPC, albeit ranked at the bottom of the list, are still considerably larger than the neutral value of 3 on a five-point Likert scale.

Table 6.4 Measurement items in analysis of construction productivity

Variable	Code	Mean	SD	Items description

Labor productivity	LP	4.01	0.64	BIM implementation has greatly enhanced construction labor productivity
Communication and coordination	CC	4.24	0.66	BIM implementation can foster communication and coordination among different project participants, thus to facilitate the construction process
Site resource planning and management	SRPM	3.82	0.64	BIM implementation has increased the efficiency of resource planning and management in a timely manner to avert redundancy or deficiency
Simulate master schedules and construction sequences	SSS	4.26	0.60	BIM implementation can predict potential conflicts and construct a reasonable construction schedule with rational construction sequences
Shorten project duration	SPD	4.40	0.62	BIM implementation can significantly save project time due to less rework, improved quality, and enhanced collaboration
Quantity takeoff and cost estimation	QTCE	4.07	0.57	BIM implementation has enabled a faster execution of quantity takeoff and cost estimation processes.
Minimize project costs	MPC	3.76	0.65	BIM implementation has enabled fewer production defects with less rework, reduced change orders to achieve cost savings.

Reliability of the constructs was tested by deploying Cronbach's coefficient alpha. The alpha levels for each of the constructs were higher than the threshold of 0.70, indicating the scales were a reliable measure to be accepted (Cronbach, 1951). A test for internal consistency and reliability of these indicators provided a satisfactory Cronbach's coefficient alpha of 0.769. A series of ANOVA tests were then performed to identify how the answers regarding productivity performance ratio (PPR) are associated with respondents' backgrounds. As shown in Table 6.5, the mean value of PPR is not statistically significantly associated with the respondents' work experience and the number of BIM-based projects involved. However, the association between years for implementing BIM and PPR is found to be statistically significant. Generally, the more experience respondents have for BIM implementation, the more benefits they would explore for productivity improvement.

Table 6.5 Results of ANOVA tests for PPR by respondents' backgrounds

Parameter	Category	N	Mean	SD		SS[a]	F-value	p-value
Work experience	Below 2	27	3.98	0.58	Between groups	1.41	1.321	0.240
	2-5	33	4.02	0.64	Within groups	43.97		
	5-10	22	4.32	0.67	Total	45.37		
	10-15	6	4.00	0.55				
	Above 15	4	4.50	0.58				
Number[a]	1-2	56	4.09	0.61	Between groups	0.59	0.427	0.734
	3-4	31	4.13	0.67	Within groups	44.79		
	5-6	11	4.00	1.00	Total	45.37		
	Above 6	4	4.50	0.58				
Number[b]	Below 1	16	3.81	0.54	Between groups	4.66	2.773	0.031
	1-3	46	3.96	0.56	Within groups	40.72		
	3-5	30	4.27	0.69	Total	45.74		
	5-7	8	4.50	1.07				
	Above 7	2	4.50	0.71				

[a]Number of BIM-based projects involved; [b]Number of years for implementing BIM; [a]SS= sum of squares.

In order to formally examine whether the survey responses were biased due to the different types of project participants, a series of ANOVA tests were then performed to assess the differences in the means of the core multi-scale variables (including PPR, LP, CC, SRPM, SSS, SPD, QTCE, MPC) among different project practitioners. The comparison results shown in Table 6.6 reveal that none of the difference is significant at the level of 5% confidence interval (p-values for the ANOVA tests for PPI, LP, CC, SRPM, SSS, QTCE, and MPC are 0.114, 0.650, 0.374, 0.458, 0.238, 0.169, 0.321, and 0.198 respectively)

Table 6.6 ANOVA tests for core variables from different types of project respondents

Variables	F-value	p-value
PPI	2.032	0.114

LP	0.619	0.650
CC	1.073	0.374
SRPM	0.886	0.458
SSS	1.433	0.238
SPD	1.715	0.169
QTCE	1.182	0.321
MPC	1.647	0.198

6.3.2 Stepwise Regression Analysis

In identifying the impacts of seven BIM-enabled potential influential indicators on construction productivity, multiple regression analysis was performed by using SPSS (Version 20) with the data from 102 respondents. Multiple regression analysis is used to analyze the relationship between a single dependent variable productivity performance ratio (PPR) and several independent variables, including labor productivity (LP), communication and coordination (CC), site resource planning and management (SRPM), SSS (simulate master schedule and construction sequences), shorten project duration (SPD), quantity takeoff and cost estimation (QTCE), and minimize project cost (MPC).

A test for internal consistency and reliability of these indicators provides a satisfactory Cronbach's coefficient alpha of 0.769. Multicollinearity is tested by the variance inflation factors (VIF), a measure that evaluates the degree of multicollinearity among the predictive variables (O'brien, 2007). Most commonly used rule of thumb associated with VIF is 10, indicating a sign of severe collinearity among potential independent variables (Draper and Smith, 2014). Standardization of the coefficient is habitually employed to address the problems that which of the predictable variables have a greater effect on the dependent variable regardless of the different units measured in the multiple regression model (Aiken et al., 1991). Regression diagnostics was undertaken to examine the appropriateness of the assumptions made by fitting a regression model to a specific set of data (Belsley et al., 2005). With the utilization of SPSS 20.0, it is found that the regression model is generally fitted under the following assumptions of linearity (the relationships between the DER and the predictive variable is linear), normality (the errors is normally distributed), homoscedasticity (the errors variance is constant), and independence (the errors associated with one observation are not correlated with the errors of any other observation). The term (R^2) indicates how much variation in the dependent variable is explained by a group of independent variables, where a higher value indicates more powerful model. In addition, only those variables with a p-value less than 5% were retained for inclusion in the final regression model equations. The adjusted coefficients of determination (adjusted R^2) are evaluated to measure the goodness-of-fit of the regression model, since it does not automatically increase with the additional predictor variables.

Stepwise regression is regarded as a powerful instrument for automatically determine the best combination of potential predictive variables that best fits the dependent variable. The results of regressions on the single dependent variable PPR and the independent variables are depicted in Table 6.7. The maximum VIF (2.368) in the Table was greatly less than the threshold point of 10, indicating that multicollinearity would not increase the standard errors of the DER model estimate (VIF ranging from 1.748 to 2.369). Multiple regression equations (RPE) with six determining factors are finally constructed as Equation 6.1. The resultant outcomes from the best-fit evaluation of multiple regression model indicated a p-value of lower than 0.05 with the associated adjusted R^2 values more than 0.7, which implied goodness-of-fit models. Results of the stepwise regression analysis revealed the value of adjusted R^2 was 0.73, indicating a good fit model. The Durbin-Watson value was 1.899, which meant the residual errors was also normally distributed.

Table 6.7 Multiple regression analysis for construction productivity gains model

Model	Construction Productivity Model					
Independent variable	Unstandardized coefficients		Standardized coefficients	t	p	Multicollinearity
	B	Standard error	β			VIF
Constant	-1.580	0.382				
LP	0.180	0.075	0.171	2.396	0.019	1.667
CC	0.165	0.061	0.164	2.705	0.008	1.191
SRPM	0.174	0.073	0.165	2.374	0.020	1.567
SSS	0.204	0.077	0.182	2.670	0.009	1.506
SPD	0.310	0.077	0.286	4.017	0.000	1.650
QTCE	0.178	0.078	0.161	2.276	0.025	1.449
MPC	0.166	0.068	0.152	2.438	0.017	1.411

Note: $P^* < 0.05$, $P^{**} < 0.01$, $P^{***} < 0.001$

As illustrated in Table 6.7, the stepwise regression analysis determined seven significant independent variables, which are all positively associated with the dependent variable PPR. These are:

LP*: *BIM implementation has greatly enhanced construction labor productivity.*

CC**: *BIM implementation can foster communication and coordination among different project participants, thus to facilitate the construction process.*

SRPM*: *BIM implementation has increased the efficiency of resource planning and management in a timely manner to avert redundancy or deficiency.*

SSS**: *BIM implementation can predict potential conflicts and construct a reasonable construction schedule with rational construction sequences.*

SPD***: *BIM implementation can significantly save project time due to less rework, improved quality, and enhanced collaboration.*

QTCE*: *BIM implementation has enabled a faster execution of quantity take off and cost estimation processes.*

MPC*: *BIM implementation has enabled fewer production defects with less rework, reduced change orders.*

Drawn on the seven determining indicators, the construction productivity improvement model was modified (and the associated valences of the standardized β weights) to demonstrate the causal relationship between the dependent and independent variables, as shown in Figure 6.1. Final model coefficients are presented in Table 6.7. The regression equation can be expressed as:

$$PPR = -1.58 + 0.180LP + 0.165CC + 0.174SRPM + 0.204SSS + 0.310SPD + 0.178QTCE + 0.166MPC \quad \text{Eq. (6.1)}$$

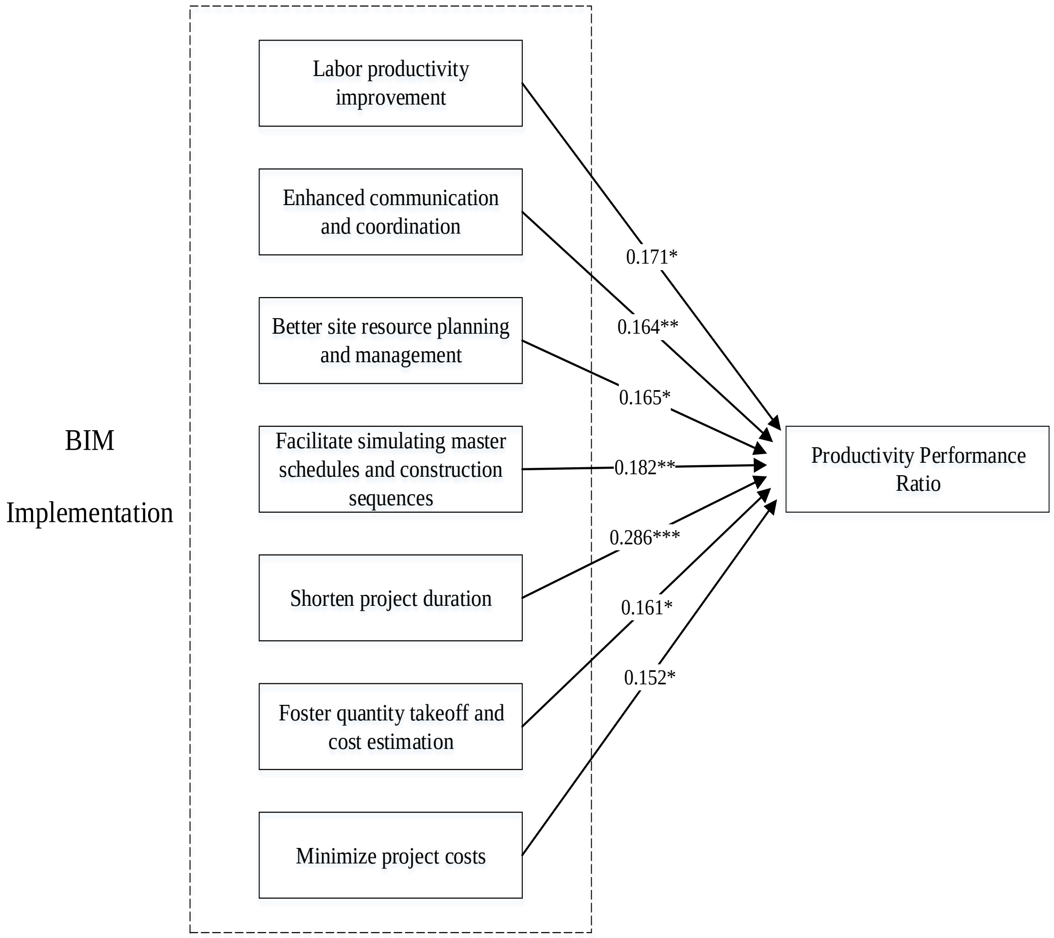


Figure 6.1 Results of multiple stepwise regression analysis of construction productivity gains model

6.4 Discussion of Findings

The increasing complexity of building designs with the development of building structures, materials, equipment indicates that only simple rules and guidelines cannot fulfill the requirements of current projects. Drawn on the conceptual framework concerning the impacts of BIM implementation on construction productivity, Chapter 6 has empirically tested the conceptual model for probing deeper into how and to what extent the contributory factors can influence the project-level construction productivity. Results of ANOVA tests indicate that the number of years of implementing BIM has positive impact on productivity performance ratio, which means the more experience respondents have for BIM implementation, the more benefits they would explore for productivity improvement. Furthermore, results from multiple stepwise regression analysis suggest that reflective constructs (incorporating labor productivity, communication and coordination, site resource planning and management, simulate master schedule and construction sequences, shorten project duration, quantity takeoff and cost estimation, and minimize project cost) are all positively statistically significant with productivity performance ratio, suggesting that, productivity performance ratio increases with these seven reflective factors. Relied on the BIM-based construction productivity gains model, results also reveal that shorten project duration (standardized $\beta = 0.286$, $p^{***} < 0.001$) has the best ability to influence productivity performance ratio through BIM implementation. In addition, simulate master schedule and construction sequences (standardized $\beta = 0.182$, $p^{**} < 0.01$) and labor productivity (standardized $\beta = 0.171$, $p^{*} < 0.05$) have also been identified as the most effective way to enhance construction productivity. Furthermore, the implementation of BIM in construction projects can have better site resource planning and management, foster communication and coordination, facilitate quantity takeoff and cost estimation. All these factors have been identified to greatly affect productivity performance ratio.

6.5 Chapter Summary

This chapter has empirically tested a research model to identify how and to what extent the impacts of BIM implementation influence construction productivity. The results from multiple stepwise regression analysis based on the 102 responses from Chinese mainland construction projects reveal that BIM-enabled shorten project duration plays an important role in impacting the BIM-enabled productivity gains. Apart from SPD, other seven control variables (including CC, SRPM, SSS, QTCE, MPC) are also found to significantly influence the productivity performance ratio of surveyed construction projects. Overall, the results provide evidence that productivity performance ratio is positively associated with the seven identified indicators.

CHAPTER 7 CONCLUSIONS

7.1 Introduction

This chapter concludes this research by summarizing the research findings and how the research propositions have been addressed. Major research findings are summarized from document analysis, model development, and model validation. Then, a summary of the contributions to knowledge in the construction industry is given. Finally, limitations of the research and recommendations for further directions are discussed.

7.2 Summary of Research Findings

This research aims to identify the impacts of BIM implementation on construction productivity. To achieve this, theoretical foundations derived from document analysis and empirical project-based data from Chinese mainland construction projects were gleaned and analyzed to investigate: (1) the extant research theories related to the status of BIM implementation and basic characteristics of construction productivity; (2) the BIM-enabled design error reduction (DER) model during design stage, as well as a conceptual framework regarding BIM-based construction productivity gains model; (3) the impacts of BIM implementation in reducing design error by using the conceptual model based on the different design error reduction (DER) indicators; (4) the conceptual model for probing deeper into how and to what extent the implementation of BIM can influence the project-level construction productivity based on the empirical data from BIM-based construction projects. The major findings of these investigations are summarized as follows.

(1) To establish the theoretical foundation of this research, extant research regarding BIM related research on the construction industry and basic characteristics

of construction productivity are examined and reviewed. The literature review provides insights into the desirability and complexities in enhancing construction productivity both in design and construction stage. Results from literature review also suggest that, not only rare empirical research has been placed on quantifying the impacts of BIM on design error reduction, and quantitatively measuring the extent to which attributable factors could have the better ability to contain design error, but sparse scholarly attention has been focused on quantitatively demonstrating the principal impacts of BIM implementation on construction productivity at project level during construction stage

(2) Document analysis is conducted to further evaluate the impacts of BIM implementation on the construction process. First, driven by the presence and severity of design error, together with the aim of elevating design productivity, a conceptual framework of design error reduction model which aims to measure the impacts of BIM implementation on productivity during design stage is developed. Results also indicate that the effective implementation of BIM in design stage could be a source of improving productivity for subsequent stages, such as construction and operation. Then, a conceptual framework of BIM-enabled construction productivity gains model is also proposed to assess the impacts of BIM implementation on construction productivity during the construction stage.

(3) With regard to the impacts of BIM in reducing design error, results from multiple regression analysis reveal that six attributable factors (including clash detection, design system coordination, drawing error, teamwork and cooperation, constructability and practicality, and facilitate knowledge and information sharing) are found to be positively statistically associated with the aggregate impacts of BIM implementation on design error reduction, among which clash detection has the best

ability to positively affect design error reduction. Noteworthy, the indicator of human error is excluded from the model due to the non-significant association with the DER. In addition, research findings also imply that BIM will considerably improve the efficiency and effectiveness of design process only by juxtaposing with other organizational and managerial project-related strategies that have been verified. Otherwise, BIM will become a sole driver for error containment, which may give rise to the failures that would impair the performance and productivity of construction projects.

(4) Drawn on the conceptual framework concerning the impacts of BIM implementation on construction productivity, Chapter 6 has empirically tested the conceptual model for probing deeper into how and to what extent the contributory factors can influence the project-level construction productivity. Results of ANOVA tests indicate that the number of years of implementing BIM has a positive impact on productivity performance ratio, which means the more experience respondents have for BIM implementation, the more benefits they would explore for productivity improvement. Furthermore, results from multiple stepwise regression analysis suggest that reflective constructs (incorporating labor productivity, communication and coordination, site resource planning and management, simulate master schedule and construction sequences, shorten project duration, quantity takeoff and cost estimation, and minimize project cost) are all positively statistically significant with productivity performance ratio, suggesting that, productivity performance ratio increases with these seven reflective factors. Relied on the BIM-based construction productivity gains model, results also reveal that shorten project duration has the best ability to influence productivity performance ratio through BIM implementation.

7.3 Contributions of the Research

Productivity is of utmost importance to the construction industry as the construction projects become increasingly fragmental to manage and control in China. In the meantime, the rapid development of China's urban construction projects brought about increased urgencies to reduce design and construction time, and to tighten project budgets and amidst more complex projects. Additionally, the prevalence of lower construction productivity and its resultant accumulative inefficiencies on the overall performance of construction projects is a leitmotiv within the construction industry. BIM as a fundamentally innovative approach of producing, sharing and exerting project lifecycle information could be applied in all stages of a construction project to support increased productivity gains.

This study makes several contributions to the extant literature on BIM and construction productivity. First, this research can enrich theoretical development in the fields of BIM and construction productivity. By reviewing the existing research, this study provides a comprehensive understanding with respect to the concepts of BIM and construction productivity. The research findings and gaps identified in previous studies could serve as the basis for recommending future research in relevant fields.

Second, as an exploratory effort to build up the relationship between BIM and construction productivity, a design error reduction model and BIM-enabled construction productivity gains model have been developed from document analyses to identify the potential relationship between BIM implementation and construction productivity both in design and construction stage.

Third, based on the investigation of the impacts of BIM implementation in reducing design error, this study modifies the original model by excluding human error, and identifies how the influential attributes affect the BIM-enabled design error reduction model in the design stage. Also, through providing empirical evidence that BIM implementation can significantly influence construction productivity in construction projects, beneficial results can be a stimulating factor facilitating construction practitioners using BIM technology in China. The findings could help to develop a more comprehensive understanding of the reasons why construction organizations implement BIM in construction projects and provide a more dynamic picture of how construction productivity may vary as the attributable factors change.

7.4 Limitations of the Research

First, the limitation of this research is attributed to the limited sample size. Since the implementation of BIM has been relatively rare in Mainland China, limited data were collected and analyzed to identify relative issues. Also, the interaction and relationship between factors are not considered in this study due to their low correlation. In addition, the results have been primarily subjective to the participants' responses. A questionnaire survey was employed as the primary means to collect perceptual data from project respondents, and no case studies were performed to validate the proposed conceptual framework. This may generate potential response biases related to subjectivity and social desirability. Finally, this study was conducted in a specific cultural and market in the Chinese mainland construction industry. This may limit the universality of the related results to other backgrounds.

7.5 Recommendations for Future Research

Future research direction could examine more relevant variables in the models and therefore develop a more comprehensive theoretical framework for understanding and assessing the impacts of BIM implementation on construction productivity. Further research could also attempt to collect project-based data from multiple sources, and use both objective and subjective data to measure the variables related to productivity gains. These could help to cross-validate the collected data and, therefore, further control the negative impacts of potential response biases on data analysis results. Furthermore, present research could be extended to cross-nation level to compare the results from different backgrounds.

7.6 Chapter Summary

In summary, this chapter systematically generalizes the major findings and highlights the significance and contributions. Then, the limitations of the current study are discussed. Finally, recommendations for future research have been proposed.

Appendix I: Questionnaire on the Impacts of BIM Implementation in Reducing Design Error

尊敬的专家：

您好，

非常感谢您能在百忙之中抽出宝贵的时间来参与此次问卷调查，本次调查以学术研究为目的，其宗旨在于调查 Building Information Modeling (BIM)技术在设计阶段对设计错误的影响及其关系。建筑信息模型（BIM）概念自引入中国以来，得到了业界与学术界的广泛认可，这一革命性，创新性的理念，在中国建筑行业掀起了一股 BIM 的应用热潮。但是国内建筑业对 BIM 的相关研究和应用仍处于探索阶段。

您的看法对这一研究课题将有非常重要的启发和帮助，因此冒昧邀请您参与此次问卷调查，给您带来的不便我深感抱歉。您所提供的信息只做学术研究之用，采用匿名回答的方式，本人将对其严格保密。问卷总共包括 2 个部分，全部完成仅会使用您 5 至 10 分钟的时间。如果您需要，我们将为您提供本次调查的汇总和分析结果，以便您了解其他专家对这些问题的看法。请将此问卷返回至 jason.zhou@ 或 270154089@ 。

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周鑫

香港理工大学建筑及房地产学系

<u>第一部分　背景资料</u> （请勾选“☒”）

1. 您所在的组织机构：

☐业主单位 ☐设计单位 ☐施工单位 ☐咨询公司

2. 您从事建筑行业的年限：

☐0-2 年　　☐2-5 年　　☐5-10 年　　☐10-15 年　　☐15 年以上

3.您的学历背景：

☐初中及以下　☐高中　☐大专　☐本科　☐硕士　☐博士

4. 您接触 BIM 的时间：

☐1 年以下　☐1-3 年　☐3-5 年　☐5-7 年　☐ 7 年及以上

5. 目前，您所参与的使用 BIM 技术的施工项目：

☐1-2 个　☐3-4 个　☐5-6 个　☐6 个以上

6. 您现在所参与的项目总合同金额为多少：

☐1 亿以下 ☐1-5 亿 ☐5-10 亿 ☐10 亿-15 亿 ☐15 亿-20 亿 ☐20 亿以上

<u>第二部分 调查问卷</u>

一、问卷说明（共 7 题）：本部分用于调查被访者通过实际工作中的经验及观察，指出 BIM 技术的应用在**设计阶段**对设计错误的**总体影响**，以及对哪些因素的影响能够有效地**减少设计错误的发生**，请**标出**您认为符合的选项：

1- 强烈不同意 2-不同意 3-中立 4-同意 5-强烈同意

BIM 应用的效果	
1. 基于 BIM 建立的 3D 可视化模型，能够有效减少设计错误发生的可能性	□1 □2 □3 □4 □5
2. 基于 BIM 建立的 3D 可视化模型，能有效进行碰撞检查，消除构件内部潜在冲突发生的可能性	□1 □2 □3 □4 □5
3. 基于 BIM 建立的 3D 可视化模型，能够有效减少人为错误发生的可能性	□1 □2 □3 □4 □5
4. 基于 BIM 建立的 3D 可视化模型，能使项目各专业进行协同设计，减少建筑各系统之间设计冲突	□1 □2 □3 □4 □5
5. 基于 BIM 建立的 3D 可视化模型，能够有效减少传统模式下，图纸经常发生的错误与疏漏	□1 □2 □3 □4 □5
6. 基于 BIM 建立的 3D 可视化模型，能够有效提高设计图纸的实际可操作性与可施工性	□1 □2 □3 □4 □5
7. 基于 BIM 建立的 3D 可视化模型，能够提高项目各参与方团队合作效率	□1 □2 □3 □4 □5
8. 基于 BIM 建立的 3D 可视化模型，能够有效促进项目各参与方，知识共享与信息交流	□1 □2 □3 □4 □5

如果您希望收到本调研的分析结果，请留下您的联系方式：

姓名：________ 工作单位：_________________

电话：________ 电子邮箱：_________________

再次感谢您的参与！

Appendix II: Questionnaire on the Impacts of BIM Implementation on Construction Productivity

尊敬的专家：

您好，

非常感谢您能在百忙之中抽出宝贵的时间来参与此次问卷调查，本次调查以学术研究为目的，其宗旨在于调查 Building Information Modeling (BIM)技术在施工阶段对建设项目生产力的影响及其关系。建筑信息模型（BIM）概念自引入中国以来，得到了业界与学术界的广泛认可，这一革命性，创新性的理念，在中国建筑行业掀起了一股 BIM 的应用热潮。但是国内建筑业对 BIM 的相关研究和应用仍处于探索阶段。

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第一部分　背景资料 （请勾选“☒”）

1. 您所在的组织机构：

☐业主单位 ☐设计单位 ☐施工单位 ☐咨询公司

2. 您从事建筑行业的年限：

☐0-2 年 ☐2-5 年 ☐5-10 年 ☐10-15 年 ☐15 年以上

3. 您接触 BIM 的时间：

☐1 年以下 ☐1-3 年 ☐3-5 年 ☐5-7 年 ☐7 年及以上

4. 目前，您所参与的使用 BIM 技术的施工项目：

☐1-2 个 ☐3-4 个 ☐5-6 个 ☐6 个以上

5. 您现在所参与的项目在哪一阶段使用 BIM:

☐设计阶段 ☐施工阶段 ☐运营维护阶段 ☐拆除改造阶段 ☐项目全寿命周期

6. 您现在所参与的项目总合同金额为多少：

☐1 亿以下 ☐1-5 亿 ☐5-10 亿 ☐10 亿-15 亿 ☐15 亿-20 亿 ☐20 亿以上

第二部分 调查问卷

二、问卷说明（共 8 题）：本部分用于调查被访者通过实际工作中的经验及观察，指出 BIM 技术在**施工阶段**对项目建设生产力的**总体**影响，以及对哪些因素的影响能够有效地提高项目建设生产力，请**标出**您认为符合的选项：

1-强烈不同意 2-不同意 3-中立 4-同意 5-强烈同意

BIM 技术的应用	强烈不同意 → 强烈同意
1. BIM 技术在施工阶段的应用，能够有效地提高项目**整体**生产力的表现	□1 □2 □3 □4 □5
2. BIM 技术在施工阶段的应用，能够有效提高项目**劳动**生产力	□1 □2 □3 □4 □5
3. BIM 技术在施工阶段的应用，能够有效促进项目各参与方协作与交流，促进生产进程	□1 □2 □3 □4 □5
4. BIM 技术在施工阶段的应用，能够合理配置劳动力，材料，设备等资源，提升资源管理及利用效率，减少资源浪费	□1 □2 □3 □4 □5
5. BIM 技术在施工阶段的应用，能够模拟与分析施工总体计划与施工顺序，合理安排施工计划和施工场地，避免工序冲突	□1 □2 □3 □4 □5
6. BIM 技术在施工阶段的应用，能够有效地减少返工，提高生产质量，从而缩短项目工期	□1 □2 □3 □4 □5
7. BIM 技术在施工阶段的应用，能够有效提高工料估算与成本预算效率，实现造价的动态控制	□1 □2 □3 □4 □5
8. BIM 技术在施工阶段的应用，能够灵活应对设计变更，减少返工，从而减少项目成本	□1 □2 □3 □4 □5
其他（请详述）:	□1 □2 □3 □4 □5

如果您希望收到本调研的分析结果，请留下您的联系方式：

姓名：__________ 工作单位：____________________

电话：__________ 电子邮箱：____________________

再次感谢您的参与！

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