Copyright Undertaking

DYNAMIC EVOLUTION AND STRATEGIC RESPONSE OF BIM ADOPTION IN THE CONSTRUCTION INDUSTRY: AN EMPIRICAL STUDY IN HONG KONG

XIAOYING LI

PhD

The Hong Kong Polytechnic University

2022

The Hong Kong Polytechnic University

Department of Building and Real Estate

Dynamic Evolution and Strategic Response of BIM Adoption in the Construction Industry: An Empirical Study in Hong Kong

Xiaoying LI

A thesis submitted in partial fulfillment of the requirements

for the degree of Doctor of Philosophy

December 2021

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgment has been made in the text.

____________________(Signed）

Name of student: LI Xiaoying

Student No: 1804

ABSTRACT

As an innovative technology to parametrically create, share, and utilize project life-cycle data, Building Information Modeling (BIM) is recognized as a promising technology to streamline traditional design and construction. Realizing the tremendous potential benefits of BIM, as pioneered by some public client organizations, the diffusion of BIM in the Hong Kong construction industry could date back about a decade ago. However, compared with leading countries, the development of BIM in Hong Kong is still at a preliminary stage and has driven the market itself.

This study aims to empirically investigate the structural characteristics of industry-level collaborative networks for BIM implementation and quantitatively characterize the dynamics of the networks, as well as explore the driving factors in different organizational innovation strategic responses. In order to achieve the research aims, longitudinal data on 192 BIM-based construction projects conducted in Hong Kong from 2002 to 2017 was first collected through a questionnaire survey and semi-structured interviews. Using the method of social network analysis (SNA) and stochastic actor-oriented models (SAOM), this thesis firstly categorized and compared the evolution of BIM collaboration networks in terms of different types of construction projects, and secondly characterized the evolution of the macro-structure of the project-based collaborative network and explored the underlying driving factors. This study also categorized strategic responses to BIM implementation. And combing with the hierarchical regression analysis result, further explored the impact of dynamic capability and social status on the choice of the strategic response on the organizational level.

This thesis has generated several significant research findings which have provided a systematical understanding of the adoption practices of innovative technology and could help facilitate the diffusion and advancement of BIM in the regional construction industry. (1) Descriptive analysis of the project-based collaborative network for BIM implementation among the 204 investigated organizations reveal that the network becomes increasingly dense over time but persistently exhibits the core-periphery structure and expands around a small number of “super-connected” nodes. This result suggests that some prominent organizations have played relatively essential roles in facilitating the diffusion of BIM-related knowledge in the Hong Kong construction industry. The result also reveals significant differences in the structure of project-based collaborative networks for BIM implementation in the regional construction industry. (2) With regard to the micro-mechanisms underlying the dynamics of the project-based collaborative network, the results of SAOM analysis provide evidence that the evolution of the macro-level network significantly relates to the structure-based preferential attachment effect and the experience-based similarity effect operating at the micro-level. It is also revealed that the individual covariate effects associated with organizational ownership type and organizational BIM experience also significantly influence the dynamics of the project-based collaborative network. (3) A better understanding of organizations’ dynamic capabilities and social status on the strategic response to BIM implementation has been achieved based on the hierarchical regression analysis. Specifically, the result demonstrated the diversity of regional organizations in terms of their strategic responses and the variety of driving factors related to the different strategic responses. And both dynamic capabilities and social status act as determinants of strategic responses from the organizational level.

The research contributes to a deepened understanding of the BIM adoption in the Hong Kong construction industry. The present study not only models the dynamic evolution of project-based collaboration networks but also quantitatively examines the roles of the similarity effect and the individual covariate effects related to organizational ownership type underlying the dynamics of project-based collaborative networks for BIM implementation. This thesis also fills the gap in the research on the strategic response to innovation from an organizational level and provides several managerial and policy implications.

LIST OF PUBLICATIONS

*This thesis contains some contents in the following article, and an asterisk * indicates the corresponding author.*

Refereed Journal Papers (Published):

1. **Li, X.,** Li, H., Skitmore, M., & Wang, F. (2021). Understanding the influence of safety climate and productivity pressure on non-helmet use behavior at construction sites: a case study. *Engineering, Construction and Architectural Management*.
2. Wu, Z., Jiang, M., Li, H., Luo, X., & **Li, X.*** (2021). Investigating the Critical Factors of Professionals' BIM Adoption Behavior Based on the Theory of Planned Behavior. *International Journal of Environmental Research and Public Health*, *18*(6), 3022.
3. **Li, X.,** Li, H., Cao, D., Tang, Y., Luo, X., & Wang, G. (2019). Modeling dynamics of project-based collaborative networks for BIM implementation in the construction industry: empirical study in Hong Kong. *Journal of Construction Engineering and Management*, *145*(12), 05019013.
4. Tang, Y., Wang, G., Li, H., Cao, D., & **Li, X.** (2019). Comparing project-based collaborative networks for BIM implementation in public and private sectors: a longitudinal study in Hong Kong. *Advances in Civil Engineering*, *2019*.
5. Li, H., **Li, X.,** Luo, X., & Siebert, J. (2017). Investigation of the causality patterns of non-helmet use behavior of construction workers. *Automation in Construction*, *80*, 95-103

Refereed Journal Papers (Under Review):

1. Yu Cao, Zesu Hua, Ting Chen, **Xiaoying Li***. Population migration and the evolution of urban spatial structure in the Yangtze River Delta region: from the perspective of social and spatial networks
2. **Xiaoying Li,** Heng Li. Categorizing and Comparing Project-Based Collaborative Networks for BIM Implementation: Evidence from Hong Kong Construction Industry
3. **Xiaoying Li,** Heng Li. Exploring the Role of Dynamic Capabilities and Social Status in Organizational Innovation Strategic Response: A Case Study in Hong Kong

ACKNOWLEDGMENT

Three years of the academic journey brought me an unforgettable experience. While writing my thesis, I had imagined countless times whom I would thank at the end. I would like to take this precious opportunity to express my deepest thanks to my teachers, colleagues, friends, and family. Without their understanding and encouragement, this thesis could not have been completed.

First and foremost, I would like to express my deepest gratitude to my supervisor, Professor Heng LI. During my MPhil and Ph.D. studies, Prof. LI act as my spiritual role model. From my initial exposure to research to defining my research direction, from the initial confusion and ignorance to the imminent completion of my Ph.D. journey, Prof. LI has always been available to selflessness helped me and continuously encouraged me. I have been fortunate to have such an extraordinary supervisor who always gave me the most valuable guidance and appreciated supervision. He taught me to be self-driven, and his great personality also influenced me in academics and personal.

Sincere and special thanks also extend to Prof. Meng Ni, who has given me selfless assistance and sustained encouragement. I would also express heartfelt thanks to my colleagues and friends at the Smart Construction Laboratory and the Department of Building and Real Estate within the Hong Kong PolyU. I am very grateful for having an opportunity to work with a group of such outstanding research colleagues throughout my study life at PolyU.

I would also like to seize this opportunity to thank my friends in Hong Kong for their company, which has brought me infinite joy and precious memories. The gratitude also goes to the experts and scholars who participated in my research for their suggestions and cooperation.

Finally, I owe my loving thanks to my parents. They have always been my spiritual pillars, my role models growing up, and the person I desire to be. Thanks for their everlasting love and support, and they mean everything to me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AEC	Architecture, Engineering, and Construction
BIM	Building Information Modelling
RBV	Resource Base View
VRIN	Value, Rare, Inimitable, And Non-Substitutable Theory
HKIBIM	Hong Kong Institute of Building Information Modelling
CIC	Construction Industry Council
RPCN	Collaborative Network for BIM Implementation in the Residential Projects
TPCN	Collaborative Network for BIM Implementation in the Transportation Projects
OPCN	Collaborative Network for BIM Implementation in the Other Types of Projects
SAOM	Stochastic Actor-Oriented Models
IC	Integrating Capability
LC	Learning Capability
RC	Reconfiguring Capability
DEC	Degree Centrality
EIC	Eigenvector Centrality
PLIS	Pioneer/Leading Innovation Strategy
FOSS	Follower/Opportunity Seeking Strategy
WSS	Wait-And-See Strategy
RAS	Resistance/ Avoidance Strategy
EFA	Exploratory Factor Analysis
OLS	Ordinary Least Square
CFA	Confirmatory Factor Analysis
CR	Construct Reliability

LIST OF ABBREVIATIONS

AVE	Average of Variance Extracted
OLS	Ordinary Least Square Regression

CHAPTER 1 INTRODUCTION

1.1 Research Background

1.1.1 Building Information Modeling as An Innovation Technology in the Construction Industry

The construction industry has been frequently criticized as slow to adopt and implement innovative technologies (Blayse & Manley, 2004; Dave & Koskela, 2009; Dubois & Gadde, 2002; Mitropoulos & Tatum, 2000). Based on some pioneering works of Tatum ((Podsakoff & Organ, 1986; C. Tatum, 1989; C. Tatum & Funke, 1988; C. B. Tatum, 1987), Nam and Tatum (C. Nam & Tatum, 1988; C. H. Nam & Tatum, 1992), and Slaughter (Slaughter, 1993), the need and approach to accelerate the rate of innovation in the construction industry has been well identified and documented (Egbu, 2004; A. Hartmann, 2006; Mitropoulos & Tatum, 1999; Stewart, Mohamed, & Daet, 2002). The traditional problem rooted in the construction industry is that the participated organizations always fail to adopt innovative technologies and processes to address the performance problems effectively in a timely manner, in particular in comparison to other sectors (Beerepoot & Beerepoot, 2007; Muchungu, 2012; Mulgan & Albury, 2003). Aware of this problem, recently, an increasing number of researchers have been focused on how to facilitate the implementation of innovative technologies in the construction industry (Kirner, Kinkel, & Jaeger, 2009; Lichtenthaler, 2011).

Digitization as a new specification in the architecture, engineering, and construction (AEC) industry has brought about a transition of design tasks from drawings to computers (Panteli, Kylili, & Fokaides, 2020). The term “Building Information Model” (BIM) was first proposed by van Nederveen and Tolman (1992) and became popularly used in 2002 (X. Li, Wu, Shen, Wang, & Teng, 2017). As an innovative technology to parametrically model and integrative manage project lifecycle information, BIM has been increasingly regarded as a promising technology to address the performance problems rooted in traditional design and construction processes (Froese, 2010; H. Li, Lu, & Huang, 2009)..

Based on its distinct characteristic of using parametric objects to model and manage project information, BIM can be used in a variety of areas such as clash detection, sustainability analysis, cost estimation, construction scheduling and offsite fabrication throughout the project life cycle (Eastman, Eastman, Teicholz, Sacks, & Liston, 2011; T. Hartmann, Gao, & Fischer, 2008). It is widely claimed that BIM, if implemented appropriately, can facilitate a more integrated design and construction process and generate substantial benefits in terms of fewer design coordination errors, more energy-efficient design solutions, reduced production cycle time, lower construction cost, and higher design and construction productivity (Bryde, Broquetas, & Volm, 2013; D. Cao, Li, & Wang, 2014; D. Cao et al., 2015; Gao & Fischer, 2008). Based on case studies in the USA and Canada, for example, it is estimated that BIM has the potential to reduce unbudgeted change orders by 37%-48% (Giel & Issa, 2013) and increase onsite labor productivity by 75%-240% (Poirier, Staub-French, & Forgues, 2015). As such, it is even claimed by Hill (2008) that BIM is driving “the most transformative evolution the construction industry has ever experienced.”

BIM has received growing interest from the construction industry in recent years. As an innovative technology that provides efficient solutions to many performance problems rooted in traditional design and construction processes (Miettinen & Paavola, 2014; Nawari, 2012). Miettinen and Paavola (2014) also pointed that as a combination of comprehensive technologies and solutions, the BIM has played a critical role in facilitating the collaboration among different sectors from an inter-organizations level. It has been shown from this review that this set of innovative technologies also helps to improve the productivity of building design, construction, and maintenance while addressing the traditional problems in the ACE industry.

To sum up, like many other innovative technologies in the construction domain, BIM is a systemic innovation, providing “an emerging technological and procedural shift in the Architecture, Engineering and Construction industry” (Succar, 2009). Simultaneously, academics and practitioners also indicated that the successful implementation of BIM in a construction project generally requires close collaboration of multiple organizations.

1.1.2 Status Quo of BIM Adoption and Application in the Hong Kong Construction Industry

Construction projects around the world have long been faced a variety of performance problems such as coordination inefficiencies, cost overruns and schedule slippages (Alinaitwe, Apolot, & Tindiwensi, 2013; Kabirifar & Mojtahedi, 2019), which collectively lead to the criticism on the construction industry as an old-type sector “forgotten by the God” (Lawrence & Dyer, 1983) and “last among equals” (Reichstein, Salter, & Gann, 2005). The construction industry in Hong Kong has not been exempt from these performance problems, as evidenced by the widely reported cost and schedule overruns in projects such as the Hong Kong Section of the Guangzhou-Shenzhen-Hong Kong Express Rail Link and the West Kowloon Cultural District in recent years. While inherently relating to industry characteristics such as the one-of-a-kind nature of construction projects, the presence of these performance problems could also be largely attributed to the conservative culture of the construction industry in adopting and implementing innovative technologies to streamline traditionally fragmented design and construction processes (Agenda, 2016; Seaden & Manseau, 2001).

Hong Kong is one of the pioneering regions globally to advocate and facilitate BIM development in the construction industry officially. While the deployment of BIM in Hong Kong could date back to more than a decade ago, when it was pioneered by some public client organizations such as the Housing Authority, the adoption of BIM in Hong Kong is still not widespread compared with leading practices worldwide. According to the latest survey conducted by the Hong Kong Polytechnic University (PICO PPR Project No.: 2016.A6.075.17A), less than 10% of the investigated corporates already involved in BIM implementation practices are implementing BIM in more than 50% of all their projects during 2016-2017, which is substantially lower than the similar rates reported in the UK (NBS, 2017) and Shanghai (COHURDM and BIMPJC, 2017). Figure 1 illustrates the comparison result in terms of BIM implementation in Hong Kong, Shanghai, and the United Kingdom by 2017. The dotted line in the graph represents the proportion of cumulative application of BIM in projects.

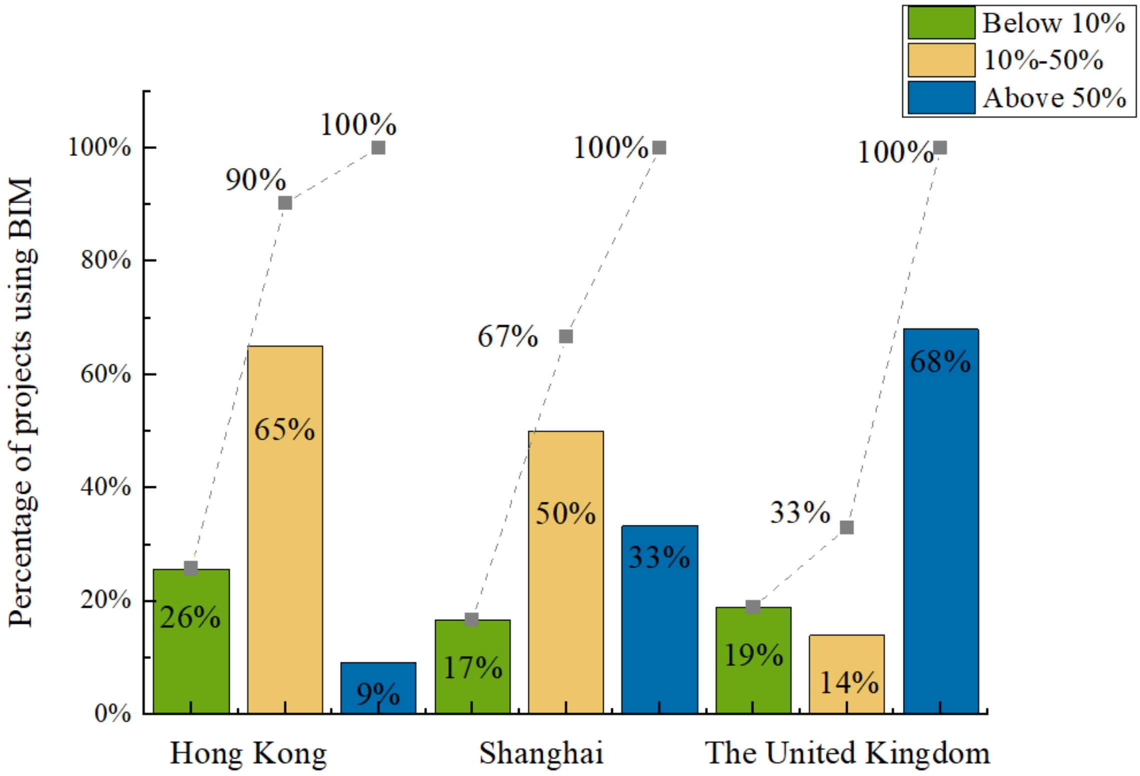


Figure 1 Percentage of projects using BIM in surveyed organizations in HK, Shanghai, and the United Kingdom

Note: (1) The percentage of organizations in Hong Kong is calculated based on the numbers of corresponding organizations' BIM-based projects identified in this study and the projects listed in the BCI database during 2016-2017, and confirmed through the interviews conducted from October 2017 to August 2018 (asking the respondents "what is the current percentage of projects in your company/organization that are using BIM in Hong Kong");
(2) The data for Shanghai are from "Shanghai BIM Technology Application and Development Report 2017", measured using the questionnaire item similar to the interview question for Hong Kong.
(3) The data for the UK is from "National BIM Report 2017", measured using the questionnaire item "percentage of projects you have used BIM for the last 12 months".

It has also been approved that the collaborative network for BIM implementation (i.e., the industry-level network that aggregates the collaborative relationships among owners, design consultants, and main contractors in different BIM-based construction projects) in the Hong Kong construction industry keeps expanding around a small number of organizations. An important part of these organizations at the core of the project-based collaborative network for BIM implementation is public client organizations. Table 1 summarizes the Top-three client organizations in the BIM-based project in Hong Kong in 2011,2013,2015.2017 and 2019.

Table 1 Top-three client organizations in the BIM-based project

Year	2011	2013	2015	2017	2019
Organization	Housing Authority	Mass Transit Railway	Mass Transit Railway	Mass Transit Railway	Architectural Services Department
	Swire Property	Architectural Services Department	Architectural Services Department	Architectural Services Department	Mass Transit Railway
	Hong Kong International Airport	Housing Authority	Housing Authority	Housing Authority	Housing Authority

And concerning the spread of BIM implementation practices among different types of industry organizations, the development of facilitating such innovative technology in Hong Kong is uneven. For example, the smaller-sized design and construction organizations generally implement BIM at lower levels in the local construction industry. As for the design consultants, as illustrated in Figure 2, 7 prominent design companies (i.e. Meinhardt Hong Kong Ltd, WSP Hong Kong Ltd, Ronald Lu & Partners Ltd, Ove Arup & Partners Hong Kong Ltd, AECOM Asia Company Ltd, Aedas Ltd, C M Wong & Associates Ltd) as core nodes in the network have assumed the design service for 67% of the total investigated BIM-based projects during the examined period, with the rest (33%) of the projects conducted by other 73 (91.56%) design consultants. Further analysis of the structure of main constrictors, as illustrated in Figure 3, similarly shows that a relatively small number of main contractors (i.e., Chun Wo Construction and Engineering Ltd, Gammon Construction Ltd, and Hip Hing Engineering Company Ltd) have conducted a relatively large proportion of the investigated projects.

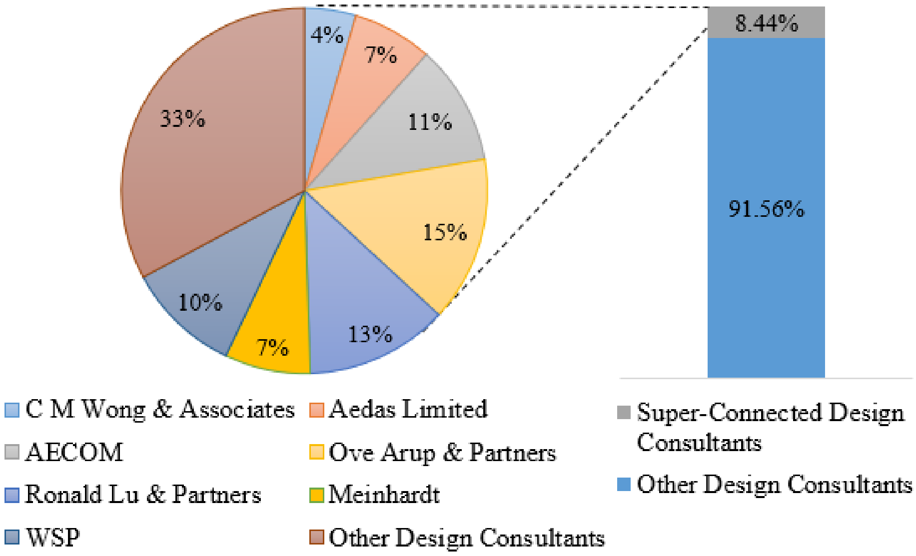


Figure 2 Proportions of BIM-based projects conducted by different design consultants

Note: The pie on the left illustrates the proportions of the total investigated BIM-based construction projects conducted by different design consultants, whereas the bar on the right illustrates the percentages of related design consultants in terms of the number of firms (core design consultants refer to the organizations specified in the pie on the left).

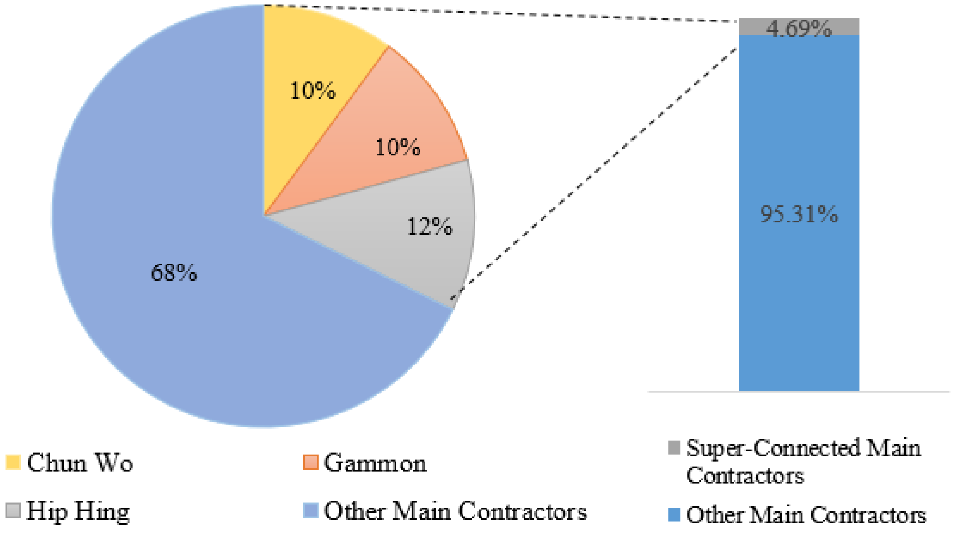


Figure 3 Proportions of BIM-based projects conducted by different main contractors

Note: The pie on the left illustrates the proportions of the total investigated BIM-based construction projects conducted by different main contractors, whereas the bar on the right illustrates the percentages of related main contractors in terms of the number of firms (core main contractors refer the organizations specified in the pie on the left).

According to the latest BIM adoption survey conducted by Construction Industry Council in 2019 (CIC 2019), 44% of organizations in the regional construction industry are adopting BIM. The top 20% of them, evaluated in terms of their BIM Diffusion & Maturity, are identified as the BIM Leaders of the Hong Kong industry; the remaining organizations are defined to be the BIM Adopters. 56% of surveyed organizations are BIM Laggers who do not have active BIM projects as of 31 Mar 2019.

In conclusion, the construction industry in Hong Kong is obviously lagging behind the leading practices countries in BIM implementation, and the adoption of BIM in regional construction remains at a primary stage. The necessity of conducting a comprehensive study relating to the implementation of BIM in Hong Kong can be drawn from the previous research to facilitate further the diffusion of this innovative technology in the regional construction industry.

1.2 Research Aim and Objectives

This study aims to systematically model the structure of collaborative networks of BIM implementation from a dynamic network perspective and to explore the organizational strategic response to innovation based on the BIM implementation practice in the Hong Kong construction industry. The specific objectives are as follows:

(1) To categorize and compare the structural characteristics of project-based collaborative networks in terms of different types of construction projects for BIM implementation in Hong Kong
(2) To empirically model the evolution of the industry-level network of project-based collaborative relationships in Hong Kong for BIM implementation over time and further explore how this evolution is influenced by a set of micro-mechanisms
(3) To investigate and assess the impacts of dynamic capabilities and social status on the innovation strategic response from an organizational level based on the implementation practices of BIM in the Hong Kong construction industry

1.3 Research Approach

In order to achieve the aforementioned research aim and objectives, this study adopted a mixed research approach, including literature review, questionnaire survey, semi-structured interviews, archival data analysis, and case-oriented analysis. As the starting point, a comprehensive literature review on BIM and observation on BIM adoption and implementation practices in the Hong Kong construction industry have been conducted to provide a foundation for the following research. Based on the review and documentary analysis study, mixed empirical methods are designed in this thesis to complete the following three research. Specifically, to categorize and compare the structural characteristics of project-based collaborative networks for BIM implementation in terms of different project types (Objective 1); to model the evolution of the industry-level network of project-based collaborative relationships for BIM implementation and explore the underlying mechanism (Objective 2); assess the impacts of dynamic capabilities and social status on the innovation strategic response of organizations in the regional construction industry (Objective 3). The overall research approach deployed in this study is depicted in Figure 4.

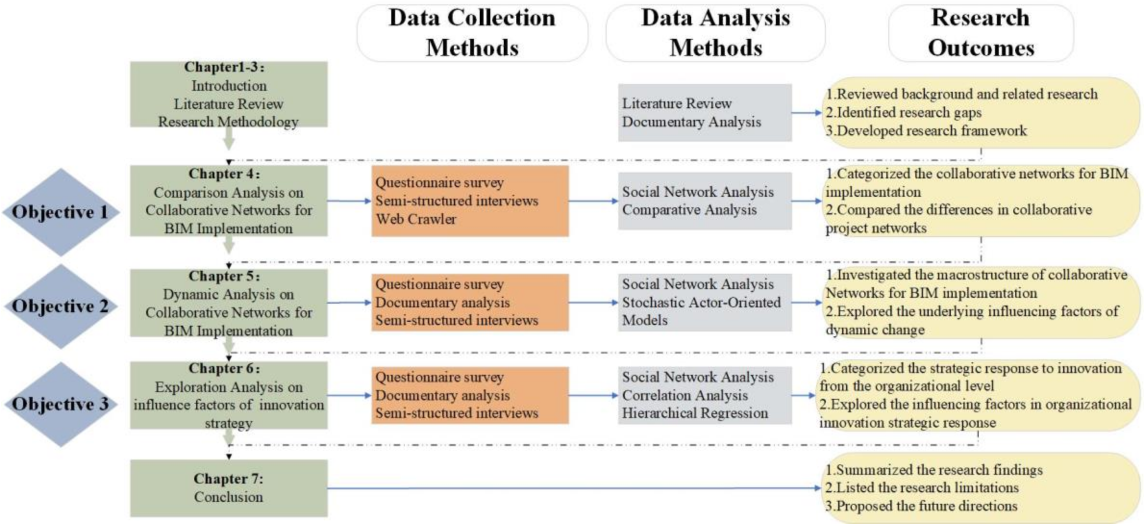


Figure 4 Research approach of the study

1.4 Research Design

After introducing the research background, including research aims and objectives, research approach, and the research design in chapter 1, the rest of this thesis is organized as follows.

Chapter 2 provides a comprehensive literature review of the potential benefits, existing barriers, and the driving factors of BIM. Moreover, the theoretical background of this research, including both social network perspective and dynamic capabilities, is demonstrated in this chapter.

Chapter 3 describes the research design and implemented data collection and analysis methodologies.

Chapters 4, 5, and 6 bring the main research contents. Specifically, Chapter 4 explores the project-based collaborative networks for BIM implementation from a comparison perspective (Object 1). Chapter 5 further models the evolution of project-based collaborative networks for BIM implementation from a social network perspective and investigate the underlying mechanism under the dynamic change (Objective 2). Chapter 6 reveals the role of dynamic capabilities and social status in the organizations' strategic response to the innovation based on the BIM implementation practices concluded in Chapter 4 and Chapter 5 (Object 3).

At last, Chapter 7 concludes the research findings and contributions of this thesis. Meanwhile, this chapter also summarizes the limitations of the current study and recommends future research directions.

1.5 Chapter Summary

The chapter briefly introduces and outlines the overall framework of this thesis, including research background, research aim and objectives, research approach, and research design.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This section will conduct a comprehensive literature review that lays the foundation for this current study. In detail, this chapter first investigates the potential benefits of BIM. Following, an overview of related studies on existing barriers and limitations of the implementation of BIM in the regional construction industry has been conducted. After exploring the driving factors of BIM adoption in the construction industry, a specific review on the BIM implementation in Hong Kong construction was conducted. Finally, the social network and dynamic capabilities perspectives have been further reviewed and designated to address the potential research question.

2.2 Potential Implementations and Benefits of BIM

In recent years, informatization has been received substantial emphasis in the construction industry. Jung, Chin, and Kim (2004) stated that information is a key resource in a construction project, facilitating effective project management and automation in engineering and construction. Furthermore, W. S. Lu, Peng, Shen, and Li (2013) argued that a particular building could be viewed as a cluster of information, and information management is critical in the process of construction project management. At the same time, lean construction and information technologies have been used in different kinds of projects (D. P. Cao, H. Li, G. B. Wang, X. C. Luo, et al., 2017). Under this background, BIM), which is regarded as a revolutionary technology for conducting effective information management during the lifecycle of a construction project, has gained growing interest from both academia and industry in recent years.

Currently, there are various definitions for BIM. For example, the National Institute of Building Sciences (NIBS) of the United States specifies that BIM is a business process for generating and leveraging building data to design, construct and operate the building during its lifecycle (NIBS, 2018). According to the National Building Specification (NBS) of the United Kingdom, BIM is regarded as a process for creating and managing information on a construction project across the project lifecycle (NBS, 2018). Though BIM has been given different literal definitions by different countries and organizations, it is widely regarded as an effective technology for construction management. Currently, the implementation of BIM has become an emerging trend in the construction industry (D. P. Cao, H. Li, G. B. Wang, X. C. Luo, & D. Tan, 2018; J. M. Li, Li, Peng, Cui, & Wu, 2018; Soust-Verdaguer, Llatas, & Garcia-Martinez, 2017; Zhao, Feng, Pienaar, & O'Brien, 2017; Zhao, Wu, & Wang, 2018). As summarized, the potential of BIM implementation and its benefits have been studied in existing literature, as shown in Table 3.

Table 2 Potential implementations and benefits of BIM

Item	Related Study
Potentials of BIM	
Cost management	Marzouk, Azab, and Metawie (2018)
Facilities management	Marzouk and Othman (2017); Parn, Edwards, and Sing (2017); Y. Tan, Song, Liu, Wang, and Cheng (2017)
Safety management	Martinez-Aires, Lopez-Alonso, and Martinez-Rojas (2018)
Green building development	Alwan, Jones, and Holgate (2017); Chong, Lee, and Wang (2017); Y. Lu, Wu, Chang, and Li (2017); Z. Ding, Liu, Liao, and Zhang (2019)
Carbon emissions calculation	Marzouk, Abdelkader, and Al-Gahtani (2017); Peng (2016); Yang, Hu, Wu, and Zhao (2018)
Life cycle energy efficiency	Eleftheriadis, Mumovic, and Greening (2017)
Prefabrication	Alwisy, Hamdan, Barkokebas, Bouferguene, and Al-Hussein (2019); Singh, Sawhney, and Borrmann (2019); T. Tan, Chen, Xue, and Lu (2019); Y. Wang, Li, and Wu (2019);
Lean construction	Saieg, Sotelino, Nascimento, and Caiado (2018); Chen, Lu, Xue, Tang, and Li (2018)
Risk management	Hossain, Abbott, Chua, Nguyen, and Goh (2018); C. Z. Li et al. (2017)
Energy retrofitting	Sanhudo et al. (2018)
Noise mitigation	Y. Tan, Fang, Zhou, Gan, and Cheng (2019)
Benefits of BIM	
Optimizing design solutions	D. P. Cao, Li, and Wang (2017); Kim and Teizer (2014); J. Wang, Wang, Shou, Chong, and Guo (2016)
Enhancing visualization	X. Y. Wang et al. (2013); Wu et al. (2019)
Improving teamwork	L. Y. Ding, Zhou, and Akinci (2014); Y. Zhou et al. (2017)

Increasing productivity	Antwi-Afari, Li, Parn, and Ewards (2018); J. H. Park and Lee (2017); Zhang, Azhar, Nadeem, and Khalfan (2018)
Saving time and expense	Love, Matthews, Simpson, Hill, and Olatunji (2014); Love, Simpson, Hill, and Standing (2013); K. C. Wang et al. (2016)
Reducing waste	Akinade et al. (2018); W. S. Lu, Webster, Chen, Zhang, and Chen (2017); J. Y. Wang et al. (2018)
Lifecycle management	L. Y. Ding and Xu (2014); J. Li et al. (2014); Luo and Gong (2015)

2.3 Existing Barriers and Limitations of the Implementation of BIM

However, in practice, despite these “theoretical” advantages, barriers and limitations were also encountered during the implementation of BIM (Gu & London, 2010; L. Liao, Teo, & Chang, 2019; L. H. Liao & Teo, 2017; Mancini, Wang, Skitmore, & Issa, 2017; Miettinen & Paavola, 2014; Succar, 2009; Venugopal, Eastman, & Teizer, 2015; Zhao et al., 2017). Regarding the technical aspect, Enshassi, Ayyash, and Choudhry (2016) claimed that the data exchange and validation have not been thoroughly investigated. Venugopal, Eastman, Sacks, and Teizer (2012) suggested that a modular and logical framework based on the formal specification of industry foundation classes (IFC) concepts should be developed. However, Y. C. Lee, Solihin, and Eastman (2019) revealed that the mechanism of data exchange standards still faces many challenges. In the non-technical aspect, Abd Jamil and Fathi (2018) argued that BIM faces legal and contractual issues during its implementation. Raouf and Al-Ghamdi (2019) reviewed BIM implementation in green buildings. The research also found that high upfront costs and delays, design complexities and documentation requirements, superior performance enhancement requirements, and skewness towards environmental sustainability were the four major obstacles in the adoption of BIM. Teng, Li, Wu, and Wang (2019) and Yu et al. (2019) stated that the profit distribution might not be fair among stakeholders.

D. Cao et al. (2015) investigated 106 real-life projects in China, revealing that BIM was principally employed as a visualization tool; the other main advantages of BIM were rarely achieved in the current AEC industry. Meanwhile, R. Jin, C. Hancock, et al. (2017) also found that lack of sufficient evaluation at the company level is a major difficulty in BIM adoption. In conclusion, although numerous foreseeable advantages of BIM can be drawn from the literature as mentioned above review, the benefits of BIM have not been sufficiently achieved in practice.

2.4 Driving Factors of BIM Adoption in the Construction Industry

To better understand the implementation practice of BIM in the ACE industry, the influencing factors of BIM adoption have been studied in the existing literature in this section. Specifically, Sun, Jiang, Skibniewski, Man, and Shen (2017) identified 22 influencing factors of BIM adoption and classified them into five categories: technology, cost, management, personnel, and legal. However, the influencing factors of BIM adoption may vary in different countries or regions. For example, Alreshidi, Mourshed, and Rezgui (2017) identified the BIM adoption barriers through semi-structured interviews in the United Kingdom and categorized the barriers into five. In detail, the barriers are divided into the social-organizational theme, financial theme, technical theme, contractual theme, and legal theme. Ngowtanasawan (2017) conducted similar research in the architectural and engineering design industry in Thailand and divided the BIM adoption factors into technology and people aspects. Meanwhile, Hatem, Abd, and Abbas (2018) identified the motivation factors of BIM implementation in Iraq, such as contracting with international experts. It is also revealed that the barriers of BIM adoption could be various in aspects, such as weakness of the government's efforts, poor knowledge about the benefits of BIM, and resistance to change.

In Hong Kong, the resistance to change by construction stakeholders was also regarded as the main barrier of BIM implementation (D. W. M. Chan, T. O. Olawumi, & A. M. L. Ho, 2019). In addition, inadequate organizational support and structure to execute BIM and a lack of BIM industry standards were considered as the other two main barriers (D. W. M. Chan et al., 2019). Ahuja, Sawhney, Jain, Arif, and Rakshit (2020) investigated the construction market in India and categorized the BIM adoption factors into three groups, namely, technological factors, organizational factors, and environmental factors. In particular, this paper summarizes the driving factors of BIM application from the following five perspectives

Individuals' behavioral intentions

Individuals' behavioral intentions towards BIM may influence its successful implementation. H. Xu, Feng, and Li (2014) tested individuals' BIM adoption behavior from three dimensions (i.e., technology dimension, organizational dimension, attitude dimension), arguing that the attitude dimension could indirectly and positively affect the actual use of BIM by enhancing their interest in learning BIM technology. Howard, Restrepo, and Chang (2017) investigated 84 industry stakeholders from the United Kingdom and found that the attitudes and intentions have direct and positive influences on the individuals’ adoption of BIM. R. Y. Jin et al. (2017) also claimed that practitioners’ perceptions towards BIM could affect its adoption.

Technical feasibility

Technical feasibility has been widely regarded as an important factor that affects the application of BIM in the construction industry. Z. K. Ding, Zuo, Wu, and Wang (2015) found that technical defects and BIM capability are the key factors that hinder architects’ implementation of BIM. To achieve four-dimensional BIM, Lopez, Chong, Wang, and Graham (2016) reviewed various technical issues concerning the usability of achieving four-dimensional BIM. Ghaffarianhoseini et al. (2017) further claimed that the definitive benefits of BIM had not been fully capitalized upon due to technical issues. Zou, Kiviniemi, and Jones (2017) also argued that existing technical limitations (e.g., incompatibility with partners) may cause risks during the implementation of BIM.

Economic viability

Economic viability is regarded as a significant factor for adopting BIM technology. D. P. Cao, Li, Wang, and Zhang (2016) examined the motives of BIM implementation, revealing that economic motives are significantly associated with the level of BIM adoption. L. H. Liao and Teo (2017) specified that advantages and financial support are critical success factors of Singapore's BIM implementation. In another study conducted by D. P. Cao, Li, Wang, and Huang (2017), the importance of economic viability was further confirmed. S. I. Lee, Bae, and Cho (2012) analyzed the economic feasibility of implementing a structural building information modeling (S-BIM) on high-rise building structures. Saieg et al. (2018) also discussed the economic aspect of adopting BIM in lean construction.

Industrial environment

The industrial environment may influence BIM adoption because coordinating various stakeholders of a project is the main advantage of BIM technology. Porwal and Hewage (2013) indicated that many clients from the public sector are afraid of using BIM in their projects because they think the market is not ready for BIM. Sacks, Gurevich, and Shrestha (2016) reviewed fifteen BIM guidelines, standards, and protocol documents and found missing aspects in some of these documents. E. Papadonikolaki and H. Wamelink (2017) argued that inter-organizational and intra-organizational conditions are important for integrating BIM with the supply chain. Recent research conducted by Abd Jamil and Fathi (2018) stated that there are still many contractual challenges to be solved for BIM-based construction projects.

Governmental supervision

Governmental supervision also plays a significant role in determining the organization's actual behavior and further affects stakeholders’ adoption of BIM by formulating regulations and policies. J. C. P. Cheng and Q. Q. Lu (2015) examined the efforts made by public sectors and argued that the public sector is always active in promoting BIM in the AEC industry. C. Y. Chang, Pan, and Howard (2017) even suggested that government can mandatorily require the compulsory adoption of BIM in public projects. In addition, as the intellectual property rights (IPR) in BIM projects are of great concern (Fan, 2014), it is necessary for the government to make relevant regulations to protect different stakeholders' intellectual property as well as other benefits.

2.5 Efforts and Roles of the Public Sector for BIM Implementation in Hong Kong

Knowing the potential benefits of BIM in addressing performance problems in traditional design and construction processes, governments or their executive arms in many regions have released relevant policies to facilitate the adoption and implementation of BIM in their construction industry. Table 3 summarizes the BIM adoption policies or strategies and the BIM implementation standards/guidelines developed in the USA, the UK, Denmark, South Korea, Singapore, and Hong Kong.

Table 3 BIM policies and adoption status in different regions

Region	Agencies	BIM policies or strategies	Adoption rate
the United States	Federal client organizations such as the General Service Administration (GSA) and the United States Army Corps of Engineers (USACE)	In 2003 the GSA established the National 3D-4D-BIM Program. In 2006 the GSA mandated BIM use in new buildings designed through its Public Buildings Service in and after Fiscal Year 2007. In 2005 the USACE conducted two pilot BIM designs; In 2006, the USACE published a BIM road map and set a goal to be "fully BIM capable" by 2012.	The adoption rate among industry practitioners climbed from 49% in 2009 to 71% in 2012.
	State governments in Wisconsin, Texas, etc.	Since 2009, local governments in Wisconsin, Texas, etc., began to mandate the use of BIM in public projects.	

the United Kingdom	Cabinet Office	In 2011 the Cabinet Office released the Government Construction Strategy, which mandated that all central government departments adopt Level 2 BIM (collaborative 3D BIM with all project and asset data being electronic) in their projects by 2016. The BIM task group was established accordingly to fulfill this aim.	The adoption rate of BIM among industry practitioners increased from 13% in 2010 to 48% in 2014.
Denmark	Danish Enterprise and Construction Authority (DECA)	In 2007 the DECA initiated the Digital Construction Program (DCP), which aims to set requirements for the use of information technologies, including BIM in public projects.	The adoption rate of BIM among industry practitioners reached 78% in 2015.
	State client organizations	Since 2007, state client organizations such as the Places and Properties Agency, the Danish University and Property Agency, and the Defense Construction Service began to follow the requirements set by the DCP to implement BIM.	
South Korea	Ministry of Land, Transportation and Maritime Affairs (MLTM)	In 2010 the MLTM released the National BIM Roadmap and National Architectural BIM Guide. In 2010 the PPS also released a BIM roadmap for public projects which mandates the use of BIM in all government projects by 2016.	The adoption rate of BIM reached 58% in 2012.
Singapore	Building and Construction Authority (BCA)	In 1995 the BCA introduced the CORENET e-submission system, which provides a solid basis for the use of information technologies, including BIM in the construction industry. In 2011 the BCA released a BIM roadmap mandating the use of BIM in all projects with more than 5000 m^2 by 2015.	The adoption rate of BIM in projects with more than 5000 m^2 should have reached 100% in 2015.
Hong Kong	Construction Industry Council (CIC) and Public client organizations	In 2014 the CIC released a roadmap to promote the use of BIM in the industry. While many organizations are still sitting on the sidelines of BIM adoption, public client organizations such as the Housing Authority (HA), the Architectural Services Department (ArchSD), and the MTR	89% of construction organizations had never used BIM or was using BIM in less than 30%

		Corporation have been relatively active in using BIM. Specifically, the HA began to use BIM since 2006 and has set a target to apply BIM in all new projects by 2014.	of projects in 2014-2015.
	Development Bureau (DEVB)	On 1 December 2017, the Development Bureau (DEVB) issued a Technical Circular (Works) No. 7/2017 on the Adoption of BIM for Capital Works Projects in Hong Kong. It is stated in the Circular that capital works projects with project estimate more than $30 Million shall use BIM technology since 1 January 2018.	N/A

Source of Data: (J. C. Cheng & Q. Lu, 2015); (G. Lee, Park, & Won, 2012); (Jensen & Jóhannesson, 2013); (Kubba, 2012); (Jóhannesson, 2009); CIC (2014); NBS (2013, 2015, 2016)

These governmental actions have spurred the innovation forward with a steady increase of BIM awareness and adoption. As a result, benefiting from the established policies and related supporting measures as well as the industry environment, according to the Smart Market Survey in 2012 and the National Building Specification (NBS) International BIM Survey in 2018, for example, the adoption rate of BIM among industry practitioners has reached 71% in the USA in 2012 (Becerik-Gerber, Jazizadeh, Li, & Calis, 2012) and 74% in Denmark in 2015 (NBS 2018). The lasted National Building Specification (NBS) report also indicated that, as one of the first countries devoted to promote the application of BIM, the overall trends of BIM awareness and adoption have grown from little more than 10% in 2011 to around 70% in 2019 (NBS 2018).

However, while governments in the aforementioned regions have established plans for the mandatory use of BIM in certain types of projects (D. Cao et al., 2014; J. C. Cheng & Q. Lu, 2015), the development of BIM in Hong Kong during the past decade was primarily driven by the market itself and diffusion of the technology among industry practitioners at present is still not widespread. According to a survey conducted by the CIC in 2014-2015, 89% of surveyed organizations in the Hong Kong construction industry had never used BIM or were using BIM in less than 30% of projects at the time of the survey (CIC 2014). It was expected that this proportion would keep at a relatively high level of 88% by 2016. With regard to the projects and practitioners that have already been involved in BIM adoption, while comparing the construction projects winning the 2012 Autodesk BIM Awards in Hong Kong with the global state of BIM implementation practices, it is also found that Hong Kong is obviously lagging behind the leading practices countries in BIM implementation and should be "strongly encouraged to keep up with the fast pace of the global adoption of BIM" (CIC, 2014, p.21).

2.6 Social Network Perspective in the Construction Industry

Similar to many other innovative technologies in the construction domain (Slaughter, 1998), BIM is a typical inter-organizational innovation. Its integrated implementation in a construction project generally requires the collaboration of multiple organizations such as owners, designers, and main contractors (J. B. Taylor, 2007). While the collaborative relationships among different organizations at the project level have the potential to substantially influence the performance outcomes of BIM implementation in the focal project (Dossick & Neff, 2010; Jin, Li, Zhou, Wanatowski, & Piroozfar, 2017), these project-specific collaborative relationships in different project contexts will also incrementally form more complex relationship networks at the industry level (D. Cao, H. Li, G. Wang, X. Luo, & D. Tan, 2018; Humphreys, Matthews, & Kumaraswamy, 2003), which are closely related to how the knowledge related to BIM diffuses among different organizations within the industry in the long term. Although recent years have witnessed increasing efforts to investigate the collaborative networks for BIM implementation within specific projects (e.g., (Al Hattab & Hamzeh, 2015; Merschbrock, Hosseini, Martek, Arashpour, & Mignone, 2018; Oraee, Hosseini, Papadonikolaki, Palliyaguru, & Arashpour, 2017; Eleni Papadonikolaki & Hans Wamelink, 2017), scant empirical evidence has been provided to characterize the network structures of project-based collaborative relationships for BIM implementation at the industry level. Recent literature suggests that project-based inter-organizational relationships substantially relate to the behaviors and performances of project-based organizations such as design and construction firms (D. Cao et al., 2018). An important theoretical mechanism used to explain these influences is the social capital theory ((Chiu, Hsu, & Wang, 2006; Putnam, 1995; Tsai, 2000). For design and construction organizations, social capital provides the opportunity to conduct project-based learning through relationship ties, and the information and knowledge gained by these ties in previous projects could facilitate these organizations to better conduct their design and construct activities in future projects (Bartsch, Ebers, & Maurer, 2013; Brady & Davies, 2004; Di Vincenzo & Mascia, 2012; Gann & Salter, 2000). According to Nahapiet and Ghoshal (1998), there are three primary dimensions of social capital as valuable resources for social action: the structural dimension, which relates to the overall configuration of social ties that link actors (Moran, 2005); the relational dimension, which refers to the mutual respect and trust that actors develop with each other through a history of interpersonal or inter-organizational interactions (L. Li, 2005); and the cognitive dimension, which refers to those resources helping generate shared norms, collective goals, and systems of meaning among actors (Tsai & Ghoshal, 1998).

As one of the most frequently used ego-level network measures in the social network analysis (Zaheer, Gözübüyük, & Milanov, 2010), degree centrality simply refers to the number of direct network connections a focal actor (called “ego”) has with other actors (called “alters”) in a network (Wasserman & Faust, 1994). In this thesis, degree centrality was used to reflect the prominent structural position in the overall network (Zaheer et al., 2010). While degree centrality counts the number of direct connections an actor has with other actors, it takes no account of the strength of the links among the organizations embedded in relationship networks (Abbasi, Wigand, & Hossain, 2014). As a construct similar to eigenvector centrality which measures the degree to which an actor connected with the well-connected actors in the overall network by assigning weights (i.e., eigenvector value) to network actors (Bonacich, 2007; Wambeke et al., 2012), the indicator of weighted centrality based on the BIM experience of network nodes was proposed in this study to reflect another structural dimension of project-based collaborative relationships in the construction industry (Tang, Wang, Li, Cao, & Li, 2019). Furthermore, the indicator of relationship superiority was also used in this thesis to measure whether an organization has collaborated with those “central” organizations which have high degree centralities. These three network measures could comprehensively reflect both the quantity and quality of the project-based collaborative relationships of design and construction organizations in the construction industry.

To sum up, knowledge learning is an important mechanism underpinning how design and construction organizations obtain social capital through project-based collaborative relationships. Specifically, the design and construction organization in the construction industry significantly differs from other types of organizations, in which the production and operation activities are mainly carried out in the form of projects (Dubois & Gadde, 2002; Hobday, 2000). As such, project-based relationship ties among the industry organizations could act as important conduits for the organizations to conduct inter-organizational learning and possess professional knowledge from project partners. Within the context of BIM implementation, specifically, having collaborative relationships with more other organizations involved in BIM-based projects, especially with those experienced organizations, could help the focal organization to better grasp BIM implementation processes and thus implement the technology at higher rates.

2.7 Dynamic Capabilities Perspective in the Strategic Management

The Resource base View (RBV) theory was first put forward by Wernerfelt (1984), describing the organizations' actions regarding leveraging or building resources to gain a competitive advantage when facing a changing environment (Colbert, 2004). Barney (1986) has further developed the RBV theory by defining the valuable resource as " must enable a firm to do things and behave in ways that lead to high sales, low costs, high margins, or in other ways add financial value to the firm." Recently, the RBV has played an essential role in strategic management, as demonstrated by its rapid proliferation in the strategy literature and other management practices (Agostini & Nosella, 2019; Barreto, 2010). RBV also emphasized that an organization's attributes related to experience, organizational culture, and competencies are the critical points to business success (Agostini & Nosella, 2019; Näyhä, 2020). The resources of organizations are rare and valuable, and to some extent, an organization's sustained performance main relies on the imperfectly imitable and imperfectly substitutable internal resources (Ainuddin, Beamish, Hulland, & Rouse, 2007; Irwin, Hoffman, & Lamont, 1998). The concept mentioned above is also known as “VRIN” criteria, which are regarded as an efficient resource for promoting firm growth. While the “Value” and “Rare” represent the basic identification of the VRIN theory, the “Inimitable” and “Non-Substitutable” focus on addressing the sustainability of organizations' performance and ensuring the long-term development of the company (Kamboj & Rana, 2021; Katsoulakos & Katsoulacos, 2007).

With the gradual increase in research on RBV, scholars have begun to argue that RVB lacks the ability to adequately describe the dynamics of uncertain environmental licensing (M. M. H. Chowdhury & Quaddus, 2017). As an extension of RBV, the concept of dynamic capability is further developed and defined as “ the firm’s ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments.” (D. J. Teece, Pisano, & Shuen, 1997). Specifically, by strategically planning appropriate resources to respond to changes in specific situations, the dynamic capability has well addressed the deficiency in a conventional RBV. Eisenhardt and Martin (2000) indicated that changes in the set of resources belonging to the company could be achieved through various modes, such as utilization, creation, access, and release.

Table 4 The framework and components of VRIN

Components	Definition	Authors (year)
Valuable	A valuable resource must generate rent which can be captured by organizations.	(Bowman & Ambrosini, 2000; Bowman & Ambrosini, 2010; Makadok & Coff, 2002; Spender, 1994)
Rare	A rare resource can help a firm generate higher profits or sales at a comparable cost to its competitors.	(Barney, 1995; Kryscynski, Coff, & Campbell, 2021; Markides & Williamson, 1996; McWilliams, Van Fleet, & Cory, 2002)
Inimitable	Inimitability arises due to the presence of segregation mechanisms, including causal ambiguity, information asymmetry, or social complexity etc. These mechanisms protect organizations from imitation of their resources and maintain the flow of rents they receive.	(Alexander, 2003; Naseer, Khawaja, Qazi, Syed, & Shamim, 2021; Spender, 2014; Zane, 2011)
Non-Substitutable	A resource is called non-substitutable if it is not readily replaceable by another resource with an identical effect. The assessment of substitutability involves an understanding of the value of the use of the resource.	(Brouwer et al., 2009; Kuhlman & Farrington, 2010; Markman, Espina, & Phan, 2004; Priem & Butler, 2001)

As one of the capabilities which avoid firms from disruption and enhance competitiveness in the long run, innovation has become a common term (Assink, 2006; Kwak, Seo, & Mason, 2018; Madrid-Guijarro, Garcia, & Van Auken, 2009). However, many organizations still find innovation elusive, especially in traditional industries such as the construction sector. Meanwhile, the invention in the construction industry can be stimulated by new requirements, regulations, or standards (de Vries & Verhagen, 2016). As announced by the Chartered Institute of Building (CIOB, 2007) in a regional report, the driving factors of the implementation of innovation can be classified as the following seven items: namely, the cost efficiency, sustainability, client demands, time constraints, technology, global competition, and end-users. Other research in the construction also identified some critical drivers of domain development, design, and realization of innovations (Bossink, 2004), such as the public policy (Qi, Shen, Zeng, & Jorge, 2010; Seaden & Manseau, 2001; Yitmen, 2007), government initiative (Bossle, de Barcellos, Vieira, & Sauvée, 2016; Tam & Tam, 2008), practice (Dulaimi, Y. Ling, Ofori, & Silva, 2002; Seaden & Manseau, 2001), and customer satisfaction (Ozaki, 2003).

Recently, the dynamic capability view fetched the attention of the researchers to study the innovation on performance at an organizational level. Meanwhile, innovation is an inevitable trend in the construction industry. Hence, the dynamic capability theory is considered an appropriate theoretical lens for exploring the various strategical responses to innovation.

2.8 Chapter Summary

This chapter presents a systematic review of current research on BIM adoption in the construction industry. The exploration of BIM is mainly from three aspects, i.e., 1) the potential implementations of BIM, 2) the benefits, barriers as well as the limitations of BIM adoption, and 3) the driving factors of BIM adoption. Based on the comprehensive review of BIM-related research, this chapter then investigates the specified situations in Hong Kong construction to provide the basis for subsequent data collection and analysis processes. The social network and dynamic capability theories reviewed in this chapter also provide a necessary theoretical background to address the three proposed research objectives.

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

As described in Section 1.2, this study aims to develop a framework to model the structure of projected-based collaborative networks and to explore the organizational strategic response to innovation based on the BIM implementation practices in the Hong Kong construction industry. To achieve the research aim, this study will consequently address three specific objectives identified in Section 1.3. This section introduced the data collection methods, data analysis methods, and data analysis tools employed to conduct related sub-studies to achieve these research objectives.

3.2 Data Collection Method

Considering the characteristics of the industry structure and BIM adoption/implementation practices in the Hong Kong construction industry, the questionnaire and interview survey will be deployed to collect data on BIM-based projects and organizational BIM adoption/implementation practices.

Due to its distinct advantages on high-efficient collecting large scale data, the questionnaire survey has been widely used in the research field of construction management (Taherdoost, 2016). A well-structured questionnaire survey among different respondents allowed the data collection process to be conducted in multiple-way (i.e., mail/internet) without distance limitations (X. Xu, Lan, Shen, Sun, & Lian, 2021). A snowballing data collection method will be deployed in the data collection to guarantee data integrity. Specifically, the questionnaire survey will firstly contact respondents from pioneering organizations in BIM adoption to identify their BIM-based projects. Then collaborators of these organizations will be contacted, and their BIM deployment situations will be studied. This snowballing process will continue until no new BIM-based projects or organizations can be further identified. In detail, the questionnaire will be dispatched to the three target groups (i.e., owners, design consultants, and main contractors) to collect data on organizational BIM adoption/implementation practices in each group. The appropriate contact persons would be the current staff in the BIM manager, technical manager, solution manager, project manager, and engineer. The structured information of the investigated organizations, including the number of full-time employees, organizational type, the year of BIM adoption, percentage of projects that are currently using BIM, the motivations and practices for organizational BIM adoption/implementation, and the strategical response to the BIM from the organizational level will be obtained from the questionnaire.

Taking into account the unique circumstances of the regional construction industry in, the information about BIM-based projects and involved organizations could also be obtained from the Hong Kong Institute of Building Information Modelling (HKIBIM), the Construction Industry Council (CIC), the BCI Asia database, and firm websites. Then, depending on the questionnaire results, follow-up semi-structured interviews will be conducted among different organizations to obtain comprehensive and detailed case-oriented data. These interviews will all be tape-recorded, and responses to the open-ended questions will then be transcribed verbatim. Whenever possible, respondents will also be requested to share possible documents, including organizational BIM development plans, project BIM implementation reports, and other materials that could help understand organizational BIM adoption/implementation practices and the strategical response to the implementation of BIM.

3.3 Data Analysis Method

3.3.1 Social Network Analysis (SNA)

Based on social capital theory, analysis of the sociological network is generally regarded as a derivation of the social structure perspectives proposed by Max Weber, Émile Durkheim, Georg Simmel or Karl Marx (Beckert, 2009). The perspective of social network analysis can be roughly divided into the following three categories: the perspectives regarding the analysis on social networks represented by White (2012), M. Granovetter (2005), and Burt (2000); the analysis from a cultural perspective proposed by Zelizer (2000); and the institution-oriented analysis advanced by Powell and DiMaggio (2012). Among them, theories regarded as most representative include the production market theory proposed by White (1981), embeddedness, the strength of weak ties theory developed by M. S. Granovetter (1973), structural holes theory created by Burt (2002), as well as N. Lin (2002) 's social capital theory (Baum & Ingram, 2002; Flap, 2002).

The theoretical perspective of networks was introduced in the 1930s and has been used in a variety of domains such as economics, politics, and sociology (Borgatti, Mehra, Brass, & Labianca, 2009). An important proposition underlying this perspective is that the structure of relations within which an actor is embedded has a significant bearing on the behaviors and performance of the actor (Zaheer et al., 2010). Due to its powerful explanatory, the network perspective has also been widely applied in the construction domain during the past three decades (Chinowsky & Taylor, 2012; Y.-S. Lee, Kim, & Lee, 2016). Examples of these applications include interpersonal communication or information exchange networks related to project success (Chinowsky, Diekmann, & Galotti, 2008; El-Sheikh & Pryke, 2010), group communication networks related to construction safety (Alsamadani, Hallowell, Javernick-Will, & Cabello, 2013; P.-C. Liao, Lei, Fang, & Liu, 2014), inter-organizational contractual relationship networks in public-private partnership projects (A. N. Chowdhury, Chen, & Tiong, 2011), inter-organizational collaborative networks for technology development or implementation (D. Cao et al., 2017; Han, Li, Taylor, & Zhong, 2018), inter-organizational collaborative networks among contractors involved in overseas or award-winning construction projects (H. Park, Han, Rojas, Son, & Jung, 2011; Tang, Wang, Li, & Cao, 2018), among others. These networks involve not only project-level networks which characterize interpersonal or inter-organizational relationships within individual construction projects (e.g., (Chinowsky et al., 2008; El-Sheikh & Pryke, 2010) but also industry-level networks which aggregate collaborative relationships in different projects as project-based macro-networks to characterize how different organizations interact with each other across projects in the long term (Han et al., 2018; H. Park et al., 2011).

Since construction projects are temporary inter-organizational coalitions and firms in the construction domain will continuously establish new project-based collaborative relationships with each other as new projects start, the project-based industry-level collaborative networks are generally more dynamic than those project-level networks that characterize collaborative relationships within individual projects (Tang et al., 2018). While recent years have witnessed increasing attempts to investigate industry-level collaborative networks in the construction industry, most of these investigations are largely based on a static network perspective, either depicting the structural characteristics of the networks in specific time periods (Y.-S. Lee et al., 2016; H. Park et al., 2011) or examining the impacts of the networks (D. Cao et al., 2018; Jason West, 2014). By contrast, relatively few studies have been conducted to characterize further how and why these industry-level macro networks evolve over time.

3.3.2 Stochastic Actor-Oriented Models (SAOM)

Recent studies on network dynamics in other domains suggest that the evolution of the macro structures of social relationship networks are closely related to a set of micro-organizing effects (Ripley et al. 2017; Snijders et al. 2010). These effects include both endogenously structure-based ones, which characterize how the changes of network ties are determined by the network structure itself, and exogenously attribute-based ones, which characterize how the changes of network ties are determined by the network nodes' attributes (Ripley, Snijders, Boda, Vörös, & Preciado, 2011; Snijders, Van de Bunt, & Steglich, 2010). Based on these studies in other domains, and taking into account the characteristics of project-based collaborative networks for BIM implementation in the construction industry, this study focuses on examining the roles of the three following effects: the preferential attachment effect related to network structures; the similarity effect related to the ownership type of network nodes; and the similarity effect related to the BIM experience of network nodes. These effects are all closely related to how project owners select design consultants and main contractors as partners in related BIM-based construction projects.

Due to its capability of statistically modeling how a set of structure- and attribute-based effects collectively influence the changes of network ties, the SAOM method has been considered to be the most promising network dynamics analysis method (Broekel, Balland, Burger, & van Oort, 2014). In SAOM, network nodes are modeled as actors that are also assumed to control the formation, maintenance, or dissolution of network ties. Based on longitudinal panel data, this method quantitatively characterizes the evolution of macro-network structures in different periods through modeling choices of actors at a micro-level. As an actor-based modeling method, SAOM is based on a set of basic assumptions (Snijders et al., 2010). First, the models in SAOM are about directed relations among the actors, where each tie has a sender (referred to as "*ego*") and a receiver (referred to as "*alter*"). The actors only control their outgoing ties. Second, the time parameter *t* in SAOM is continuous, but the parameter estimation procedure assumes that the change of network structures is observed only at two or more discrete points in time. Third, the change of network structures is modeled as a Markov chain. As such, the network at time *t+1* is probabilistically determined by its structure at time *t* but not directly influenced by its structures at *t-1* or *t-2*. Fourth, the transition of macro network structures at one time (also called "wave" in SAOM) to the next is composed of a sequence of probabilistic mini-steps. In each mini-step, one specific actor is probabilistically selected and gets the opportunity to change (or not change) one of her/his outgoing ties in the network. Fifth, the model is built upon the idea that actors can change their ties with other actors at stochastically determined moments. This change opportunity process is determined by the rate function, which models the speed by which each network actor gets an opportunity for changing (or not changing) one of her/his outgoing ties. Sixth, given that an actor has the opportunity to make a relational change, the choice for this actor is to change her/his outgoing ties depending on the effects related to network structures and actors' attributes.

Based on these assumptions, parameters in SAOM models are estimated from longitudinal network data by statistical procedures implemented by computer simulations of the network change process (Ripley et al., 2011). The first observed network is used as the starting point for the simulations. The tie variables constitute the network, represented by its $n \times n$ adjacency matrix $x = (x_{ij})$ (self-ties are excluded), where n is the total number of actors. The changes in these tie variables are the dependent variables in the estimation process. At the core of the estimation process is the *objective function*, which probabilistically determines the changes of network ties made by the actors. Each actor will change her/his ties to maximize the value of her/his objective function. The probability of an actor making a change is proportional to the exponential transformation of the objective function of the new network resulting from this change. The objective function is modeled as a linear combination of effects related to network structures and actors' attributes (Snijders et al., 2010):

$$f_i(\beta, x) = \sum_k \beta_k \, s_{ki}(x)$$

where $f_i(\beta, x)$ is the value of the objective function for actor i (the ego), which relates to the state x of the network, $s_{ki}(x)$ are the effects influencing the change of network ties, and weights β_k are the statistical parameters of each effect. The effects $s_{ki}(x)$ can relate to not only the structure of the network (*structure-based effects* such as *the preferential attachment effect*), but also the attributes of individual actors (*individual covariate effects* such as *the covariate-ego effect*) or the attributes of pairs of actors (*dyadic covariate effects* such as *the similarity effect*). The weights β_k of these effects are estimated by the mean of an iterative Markov chain Monte Carlo algorithm based on the method of moments (Snijders 2001). The stochastic approximation algorithm simulates the network dynamics and estimates the weights β_k that minimizes the deviation between observed and simulated networks. Over the iteration procedure, the provisional parameters are progressively adjusted to minimize the deviation. The parameters are then held constant to their final values to evaluate the goodness of fit of the model and the standards errors. If $\beta_k = 0$, the corresponding effect has no influence on the network dynamics. If $\beta_k > 0$ there will be a higher probability of network evolution moving in the direction where the corresponding effect is higher; if $\beta_k < 0$ the reverse applies. The estimates of β_k based on the simulation algorithm are approximately normally distributed, so the estimated parameters can be tested by referring the t-ratio (which is defined as parameter estimate divided by standard error) to a standard normal distribution (Snijders et al., 2010). The data analysis process of the evolution of project-based collaborative networks has been demonstrated in Figure 5.

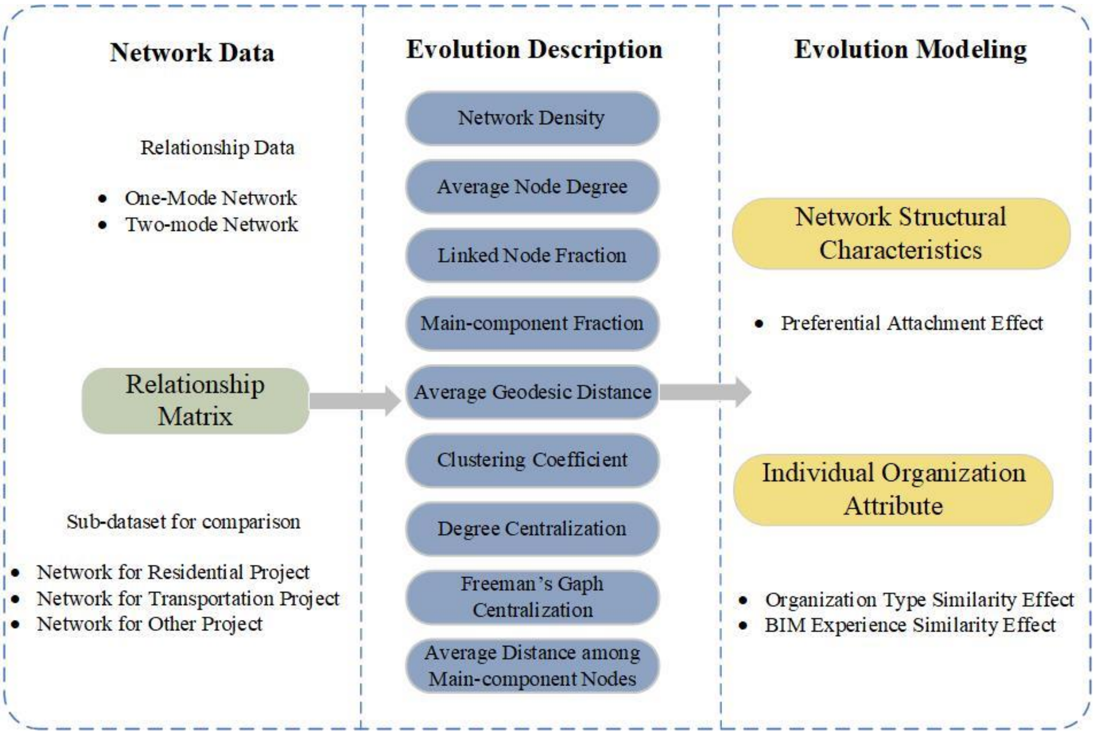


Figure 5 Data analysis process of the evolution of project-based collaborative networks for BIM implementation

3.5 Chapter Summary

In conclusion, this chapter has introduced the research design and methodology for the thesis. This chapter consists of two main parts: the data collection method, including the web crawler, questionnaire survey, and semi-structured interview, are first described in section 3.2. After discussing the data collection procedure, the detailed data analysis process for each sub-studies is provided in section 3.3. In particular, the data collection and analysis process for the analysis of the evolution of project-based collaborative networks for BIM implementation has been well designed. This chapter has provided the detailed research methodology for the three subsequent research. Based on the data collection method and data analysis method described in this section, the main research body of this thesis has been well organized in the following three chapters.

CHAPTER 4 Categorizing and Comparing Project-Based Collaborative Networks for BIM Implementation

4.1 Introduction

Different from many other industries, the construction industry is a specific project-based sector consisting of multiple types of projects (Whyte, 2003). The multiformity of the construction project can be distinguished by the type (e.g., residential project, transportation project, commercial project, and infrastructure project), complexity, or size of the project (Müller, Geraldi, & Turner, 2011). Recently, a growing number of studies point out that project types have different impacts on organizational performance (Damanpour, Walker, & Avellaneda, 2009). Developing management processes based on different project characteristics contributes to improving the effectiveness of both projects and organizations (Martinsuo, Hensman, Artto, Kujala, & Jaafari, 2006; Wells, 2012). Meanwhile, the completion of different kinds of projects usually requires close cooperation among different organizations such as owners, designers, and main contractors (Behera, Mohanty, & Prakash, 2015).

With the rising awareness to promote innovation in the industry, the development of BIM in Hong Kong has been rapidly growing in recent years. Given the fact that the adoption of BIM in regional construction was first promoted by the government and piloted in public housing projects, there is an uneven development of BIM regarding differences by project type over time. In other words, the regional market exists differences among project types in terms of the maturity and depth of the BIM implementation practice. However, the research on the comparison in terms of project types is still in its infancy. Based on the social network analysis and longitudinal data on BIM-based construction projects undertaken during 2008-2017, this section aims first to categorize the project according to the types and further compare the collaborative networks for BIM implementation in different project types. In more detail, the BIM-based collaboration network was classified into three types, namely, the collaborative network for BIM implementation in the residential project (i.e., RPCN), and the collaborative network for BIM implementation in the transportation project (i.e., TPCN), and the collaborative network for BIM implementation in the other types of projects (i.e., OPCN). Following the descriptive analysis of the dynamic evolution of the three kinds of the collaborative network was conducted respectively. Finally, a comparison study was undertaken to explore the potential different characteristics of the three types of collaboration networks.

4.2 Research Method

4.2.1 Longitudinal Data on BIM-Based Construction Projects in Hong Kong

Compared with the construction industries in other regions, such as the Chinese mainland and the USA, the construction industry in Hong Kong is relatively small in size. The particular characteristic increases the feasibility of collecting related project data to analyze the project-based collaborative networks among different organizations in the regional construction industry. And especially the case for the collaborative networks for BIM implementation, as the diffusion of BIM in Hong Kong is still not widespread and only a limited number of owners, design consultants and main contractors have been involved in BIM implementation practices. Among these involved organizations, moreover, many are large-scale corporations or institutions that play important roles in the regional construction industry in Hong

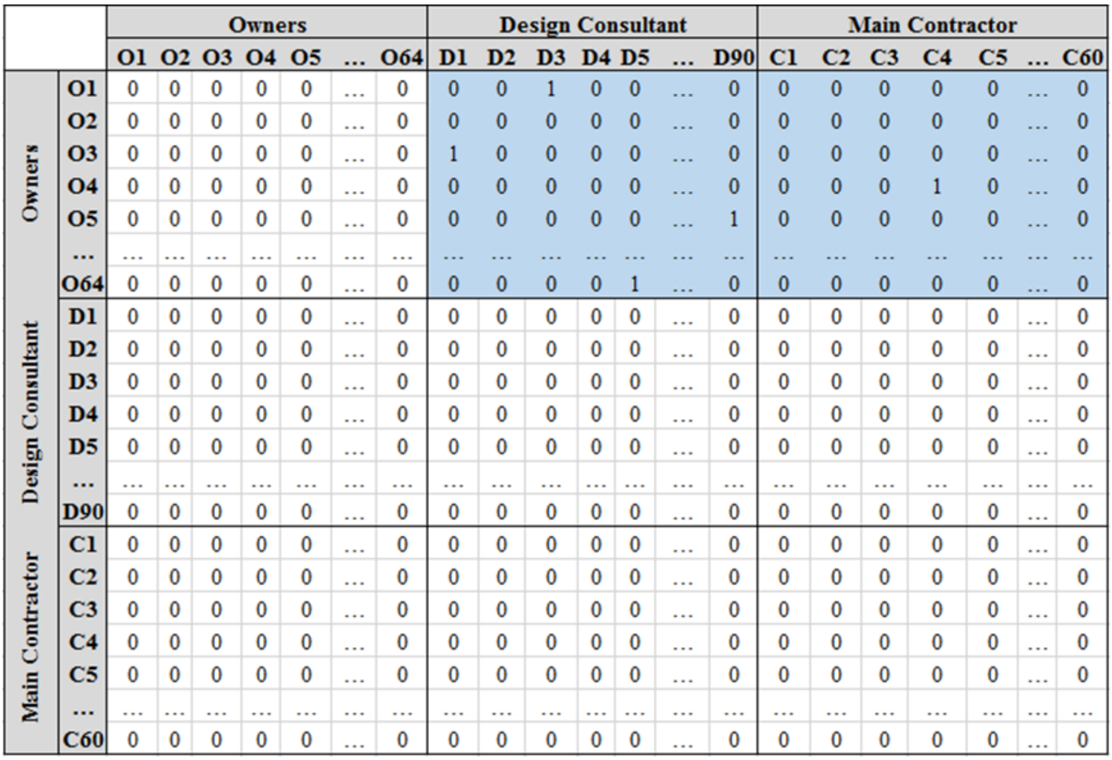
Kong (A. K. Wong, Wong, & Nadeem, 2011; K. d. Wong & Fan, 2013), including client organizations such as the Housing Authority (HA) and the Architectural Services Department (ASD), design consultants such as AECOM and Arup, and general contractors such as the China State Construction Engineering and Gammon Construction. As such, it would be feasible to use the snow-balling method based on these organizations and related project databases to further identify other organizations involved in BIM-based construction projects in the regional construction industry.

Based on the correspondence information obtained from the Hong Kong Institute of Building Information Modelling (HKIBIM), organizations winning the Autodesk Hong Kong BIM Awards during the past decade were first contacted through telephone or onsite visits. Semi-structured interviews were conducted with BIM directors or other informed professional individuals in these organizations to identify the lists of their BIM-based construction projects, the names of other organizations involved in BIM implementation in these projects, the areas of BIM implementation in these projects, and organizational BIM implementation motivations and strategies in these projects. Further information on these projects (i.e., project size, project type, project starting year, and project participating organizations) and involved organizations (i.e., locations of headquarters) was obtained from the BCI Asia database and firm websites. Other related organizations were then further contacted based on the snowballing process until no new BIM-based construction project could be further identified. This process resulted in the successful collection of the basic data of 192 BIM-based construction projects started during 2008-2017, involving 204 organizations (i.e., owners, design consultants, and main contractors) participating in the BIM implementation processes. Among the 192 construction projects, there are 69 residential projects, 45 transportation projects, and 78 other projects. Among these 204 organizations, a total of 83 organizations that are considered to be relatively active in BIM implementation in the regional construction industry were interviewed for data collection or confirmation. The collected data set is supposed to have satisfactorily covered the large majority of BIM-based construction projects in Hong Kong during the examined period. Table 5 illustrates the demographic information of three kinds of projects and the participated owners, design consultants, and main contractors involved in the BIM implementation processes of these projects.

Table 5 Demographic information of the investigated three types of project

Variable	Category	Number	Percentage
Residential Project		69	35.94%
Project commencement year	2008-2013	14	20.29%
	2013-2015	19	27.54%
	2015-2017	36	52.17%
Role of project participating organizations	Owner	20	25%
	Design consultant	39	48.75%
	Main contractor	21	26.25%
Transportation Project		45	23.44%
Project commencement year	2008-2013	16	35.56%
	2013-2015	15	33.34%
	2015-2017	14	31.10%
Role of project participating organizations	Owner	14	19.44%
	Design consultant	25	34.73%
	Main contractor	33	45.83%
Other Project		78	40.62%
Project commencement year	2008-2013	21	26.92%
	2013-2015	24	30.77%
	2015-2017	33	42.31%
Role of project participating organizations	Owner	38	29.01%
	Design consultant	61	45.56%
	Main contractor	32	24.43%

Taking into account the characteristics of the project-based collaborative networks among owners, design consultants and main contractors, the relational data among the involved organizations were expressed in two types of matrices, which are both one-mode matrices (i.e., actor-actor matrices) composed of 204 rows (i.e., the number of organizations involved in the project-based collaborative networks) and 204 columns. The first type of matrix is to reflect the macro structures of the project-based collaborative networks for BIM implementation among the investigated organizations. Each cell r_{ij} in these matrices for different time windows represents the number of projects in which the organization in the ith row and the organization in the jth column have collaboratively used BIM and thus established inter-organizational collaborative ties. Due to the reciprocal nature of the collaborative ties for BIM implementation, these matrices are symmetrized and the reflected collaborative ties are undirected. The second type of matrix is to characterize the effects driving the dynamics of the collaborative networks among the investigated organizations. Since the formation of the project-based collaborative relationships for BIM implementation among owners, design consultants and main contractors is determined by how owners selected design consultants and main contractors as their partners in related BIM-based construction projects, this type of matrix only represents the directed collaborative ties from owners to design consultants and main contractors. Therefore, the structure of this type of matrix is asymmetric. Each cell r_{ij} in these matrices that describe the collaborative ties from owners (i.e., in the ith row) to design consultants or main contractors (i.e., in the jth column) represents the number of construction projects involving collaborative BIM implementation, whereas the cells describing the collaborative ties from design consultants or main contractors were all set as 0. The sample of configurations of the one-mode matrix of collaborative ties is illustrated in Figure 6.



		Owners							Design Consultant							Main Contractor						
		O1	**O2**	**O3**	**O4**	**O5**	**…**	**O64**	**D1**	**D2**	**D3**	**D4**	**D5**	**…**	**D90**	**C1**	**C2**	**C3**	**C4**	**C5**	**…**	**C60**
Owners	**O1**	0	0	0	0	0	…	0	0	0	1	0	0	…	0	0	0	0	0	0	…	0
	O2	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	O3	0	0	0	0	0	…	0	1	0	0	0	0	…	0	0	0	0	0	0	…	0
	O4	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	1	0	…	0
	O5	0	0	0	0	0	…	0	0	0	0	0	0	…	1	0	0	0	0	0	…	0
	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
	O64	0	0	0	0	0	…	0	0	0	0	0	1	…	0	0	0	0	0	0	…	0
Design Consultant	**D1**	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	D2	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	D3	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	D4	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	D5	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
	D90	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
Main Contractor	**C1**	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	C2	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	C3	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	C4	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	C5	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0
	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
	C60	0	0	0	0	0	…	0	0	0	0	0	0	…	0	0	0	0	0	0	…	0

Figure 6 One-mode matrix of collaborative ties

4.2.2 Descriptive Network Indicators

To investigate the dynamic evolving networks in of BIM implementation in different types of construction projects in the Hong Kong industry during different time frames, the social network analysis was adopted to conduct the descriptive network analysis. The descriptive network indicators specifically used in this section are listed in Table 6. These indicators have been widely used in previous studies to describe the structural characteristics of inter-organizational collaborative networks both in the construction industry (J. Lee & Bonk, 2016; Shelton et al., 2019) and other industries (Hanaki, Nakajima, & Ogura, 2010).

Table 6 Key indicators for descriptive network analysis

Indicator	Definition and Explanation
Overall Network Indicator	
Network Density	Network density reflects the proportion of the actual linkages compared to the theoretical maximum number of possible linkages in a network. The values of this indicator can range from 0 to 1, with values closer to 1 indicating greater interconnectedness among network nodes.
Average node degree	The average node degree refers to the average number of connected ties per network node. This indicator reflects the tightness of a network.
Linked node fraction	The linked node fraction refers to the ratio of the number of linked nodes to the whole nodes in a network.
Main-component fraction	The main component in a network is the component with the largest number of linked nodes. The main-component fraction refers to the proportion of the nodes in the main component to the nodes in the whole network.
Average Geodesic Distance	The average geodesic distance refers to the average of all the geodesic path lengths between pairs of nodes. The average geodesic is widely used to represent the whole network cohesion, where a lower value represents a closer connection among nodes in the network.
Clustering coefficient	The clustering coefficient of a node (i.e., local clustering coefficient) in a network measures the density of the neighborhoods connected to the focal node. The clustering coefficient of the entire network (i.e., global clustering coefficient) is calculated as the average of the clustering coefficients of all the nodes. The coefficient indicator used in this study is the global clustering coefficient. This indicator, together with the average distance among main-component nodes, can reflect whether a network exhibit small world properties (Watts and Strogatz 1998).
Degree Centralization	Centralization measures the degree of centrality of the

	network. This indicator reflects the compactness of a network from the perspective of the core nodes, and the value is conventionally normalized from 0 to 1.
Ego Network Indicator	
Degree Centrality	Degree Centrality measures the number of links directly attached to a node; a higher value of degree centrality represent a more central position than a node occupied
Eigenvector centrality	Eigenvector centrality measures the influence of a node in the ego network, whereas connecting to a high score node has a more significant impact on the node itself than connecting to a low score node.

Based on the overall network and ego network, this section aims to provide a comprehensive analysis of the three kinds of construction projects in the regional construction industry. The research framework of this section is illustrated in Figure 7.

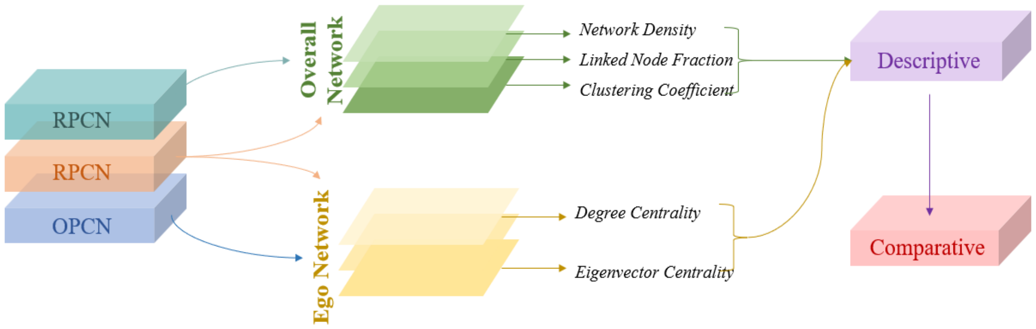


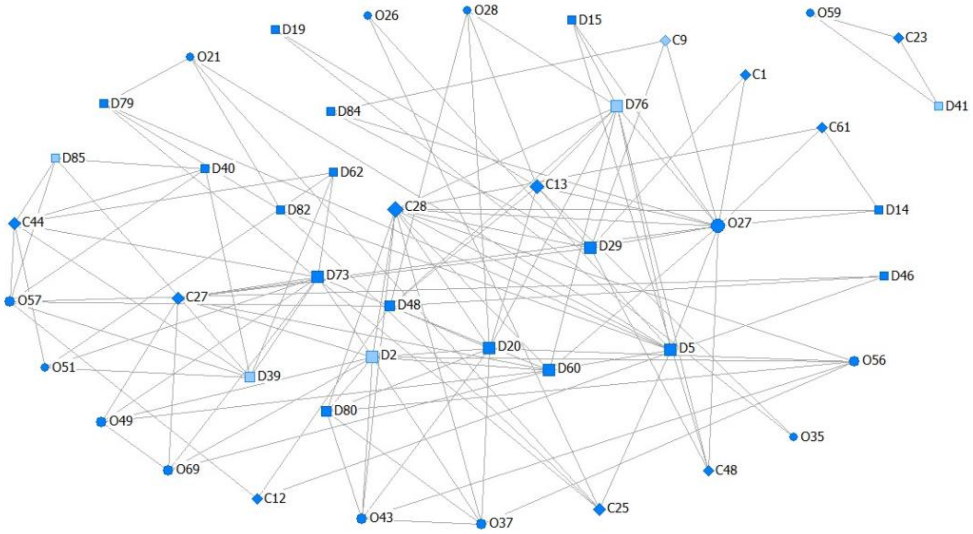
Figure 7 The research analysis process of collaborative networks of different project types

4.3 Data Analysis Result

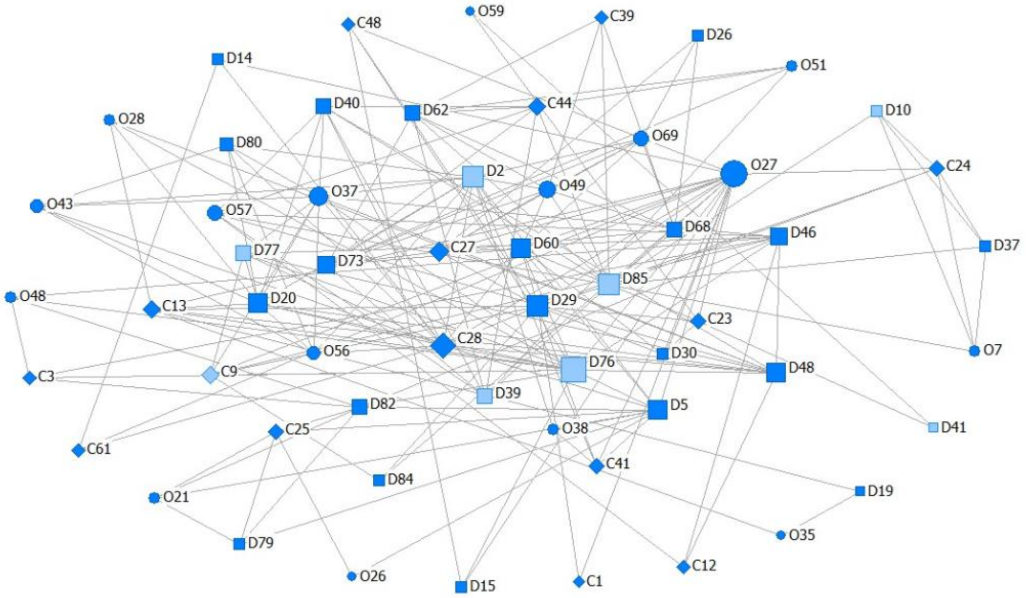
The descriptive analysis of the structural characteristics of the project-based collaborative networks was implemented with UCINET 6.636 and its visualization package NetDraw (Hanneman & Riddle, 2005). In order to investigate the dynamic evolution of the collaborative networks in different kinds of BIM-based projects during 2008-2017, this structure of the project was observed at three time points: 2013, 2015 and 2017, with each network only covering the inter-organizational collaborative relationships which were formed in the projects, started before or in the observed year. The year 2013 was set as the first examined time point because the number of BIM-based projects in previous years are too small to conduct related network analysis. Based on the relational matrices describing the undirected collaborative ties among owners, design consultants and main contractors in the investigated projects, the aggregated collaborative networks up to the three observed years (namely 2013, 2015 and 2017) of PPCN, TPCN and OPCN are plotted in Figure 8 to Figure 10. Different shapes of network nodes in the figure represent different project-participator types of the examined organizations: circles represent owners, squares represent design consultants, and diamonds represent main contractors. Different colors of network nodes represent different organizational ownership types: nodes in the dark blue represent local companies, whereas nodes in light blue represent overseas companies. Different node sizes reflect different degrees of the network nodes (i.e., the number of network ties linked to the focal node).

4.3.1 Results of Descriptive Analysis on Network Structure of RPCN

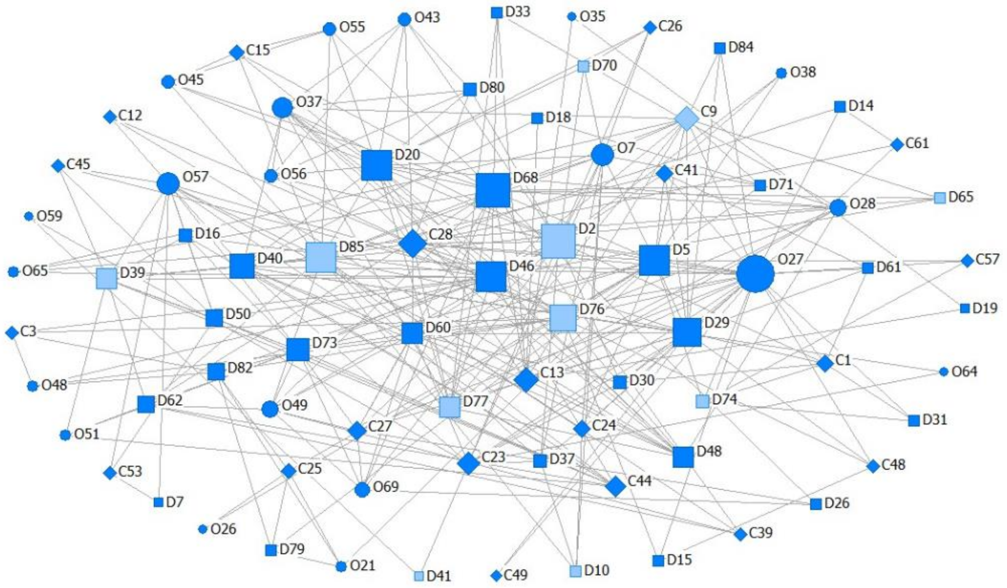
As visualized in Figure 8, with the increasing number of nodes involved in the RPCN over time, the network expands rapidly and shows an increasingly concentrated tendency. To further investigate the change of network structures in the residential project, a set of statistics calculated has been demonstrated in Table 7.



(a) network structure in 2013



(b)) network structure in 2015



(c) network structure in 2017

Figure 8 Evolution of network structure of RPCN

It is evident from Table 7 that although the network density has been in a relatively low range, the network density, average node degree, and linked node fraction have been increased during the examined time, with the value of linked-node fraction in 2017 being twice as high as in 2013. The increment of such indicators reflects an increasing tendency in the adoption of BIM in the residential project, and the influential organization in the early collaboration network is found to show a strong influence in the late collaboration network. It is also evident from Table 7 that although the main components fraction has increased, the average geodesic distance has slightly decreased over time. Specifically, the average geodesic distance between nodes was 2.619 in 2013, and it declined to 2.451 in 2017. Together with the moderately dense feature and the high clustering coefficient of the RPCN, the generally small average geodesic distance indicates small-world properties in the RPCN (Watts & Strogatz, 1998).

As shown in Figure 8, an increasing number of nodes occupied the central position in the PPCN, including local and overseas designers and local owners. This also can be approved in Table 7, with the degree centralization increased from 0.203 in 2013 to 0.240 in 2017, the clustering coefficient slightly decreased during the examined period. Hence, the collaboration network shows a distinct core-periphery structure, indicating an increasing tendency for BIM implementation in the residential project to be developed around some central nodes. The core-periphery tendency has been further conducted through the algorithm proposed by (Borgatti & Everett, 2000). As shown in Table 8, the analysis results indicate a core-periphery structure has exhibited during the whole examined period, and the super-connected nodes in the core only account for 17.72% at the end of 2017, where the vast majority of the remaining observed organizations are sparsely connected nodes distributed in the periphery.

Table 7 Evolution of network structure for RPCN: Descriptive analysis results

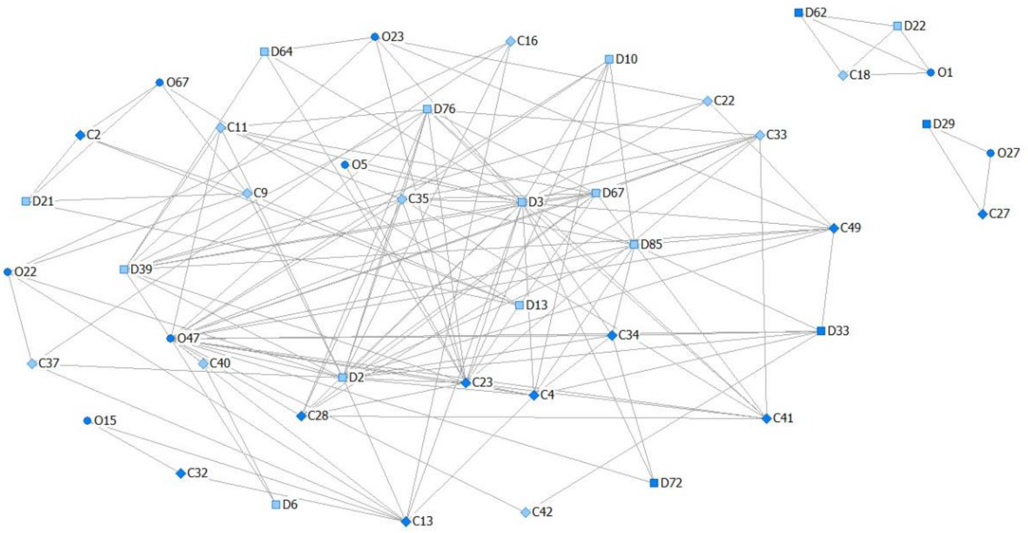
Indicator	2013	2015	2017
Nodes Number	45	58	79
Liked tie number	246	392	610
Network Density	0.124	0.119	0.099
Average Node Degree	5.4767	6.759	7.722
Linked-node Fraction	0.570	0.734	1.000
Main-components Fraction	0.532	0.734	1.000
Avg Geodesic Distance	2.619	2.546	2.451
Clustering Coefficient	0.795	0.716	0.727
Deg Centralization	0.203	0.222	0.240

Table 8 Core-periphery structure in RPCN

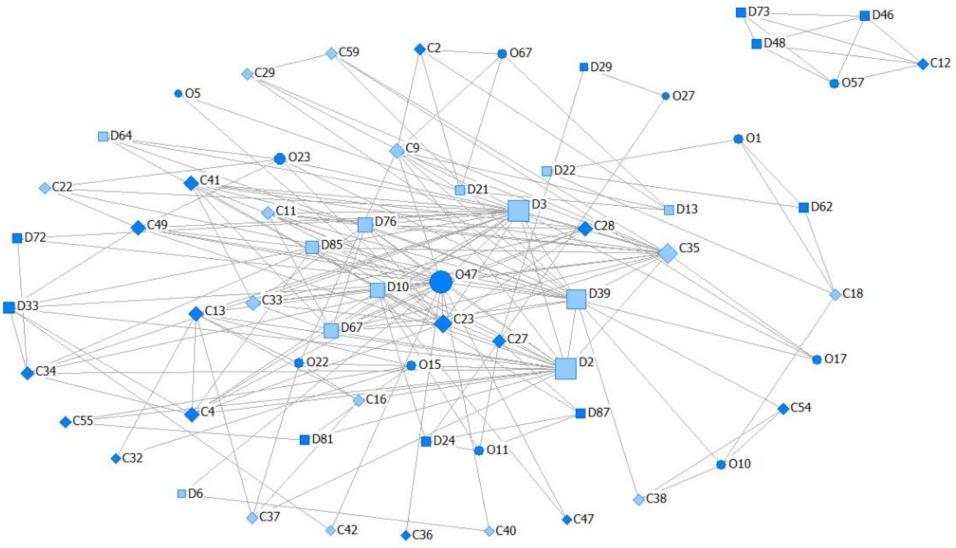
Time Points	Density of linkages		Number of nodes in the core	Final fitness
	Core	Periphery		
2013				
Core	0.891	0.138	11	0.632
Periphery	0.138	0.089		
2015				
Core	0.848	0.100	12	0.567
Periphery	0.100	0.1064		
2017				
Core	0.725	0.091	14	0.512
Periphery	0.091	0.052		

4.3.2 Results of Descriptive Analysis on Network Structure of TPCN

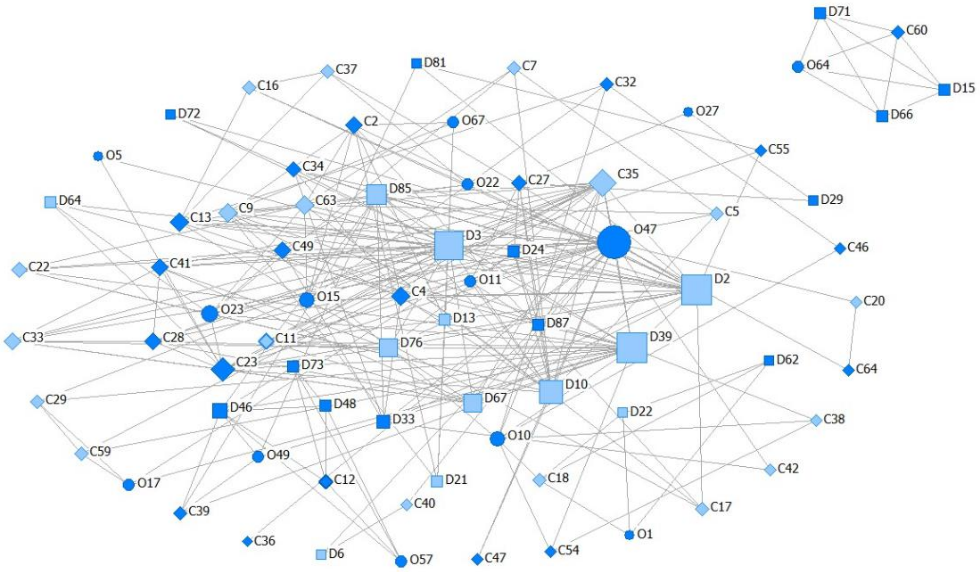
With regard to the collaborative network of TPCN, the evolution of network structure was also measured at the time points of 2013, 2015, and 2017. The dynamic change of the network structure is visualized in Figure 9. As demonstrated in Figure 9, the network structures become more cohesive during the examined time. There are several core nodes in the network, and the network expands externally around these core nodes. The statistical result demonstrated in Table 9 also plotted that the network density and the linked node fraction gradually increased over time, with the linked node fraction has reached 100% in 2017. As for the average node degree, the value has declined in fluctuations. Hence, the organizations that adopt BIM in transportation projects progressively become more and more over time. The rapid expansion of TPCN in the later stages is influenced by the organizations that applied BIM in the earlier networks.



(a) network structure in 2013



(b) network structure in 2015



(c) network structure in 2017

Figure 9 Evolution of network structure of TPCN

Table 9 also provides clear evidence that the main components fraction and average geodesic distance increased over time, where the main components fraction and average geodesic distance reached 0.934 and 2.719 in 2017, respectively. This result indicates the distance for each organization to connect with any other organization in the main component of the network, and the direct connections between two organizations are both less than three steps on average. With regard to the clustering coefficient, the value has slightly decreased over time. Regarding the core-periphery structure in TPCN, the percentage of core nodes has increased over time and reached 30.26% in 2017. As shown in Table 10, the proportion of core nodes that dominate the network is still tiny, and the majority of organizations are still at the edge of the network structure. Together with the decline of degree centralization in the TPCN, the statistical analysis result has proved that the network exhibits distinctive small-world characteristics, and links in the network are connected around several super connect nodes.

Table 9 Evolution of network structure for TPCN: Descriptive analysis results

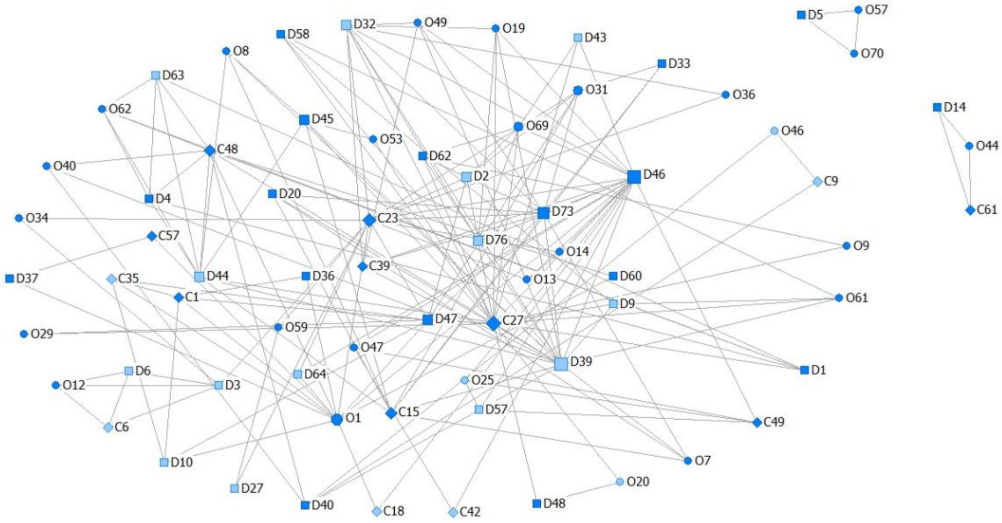
Indicator	2013	2015	2017
Nodes Number	44	62	76
Liked tie number	292	388	486
Network Density	0.154	0.103	0.085
Average Node Degree	6.636	6.258	6.395
Linked-node Fraction	0.579	0.816	1.000
Main-components Fraction	0.487	0.750	0.934
Avg Geodesic Distance	2.204	2.718	2.719
Clustering Coefficient	0.840	0.831	0.812
Deg Centralization	0.374	0.317	0.282

Table 10 Core-periphery structure in TPCN

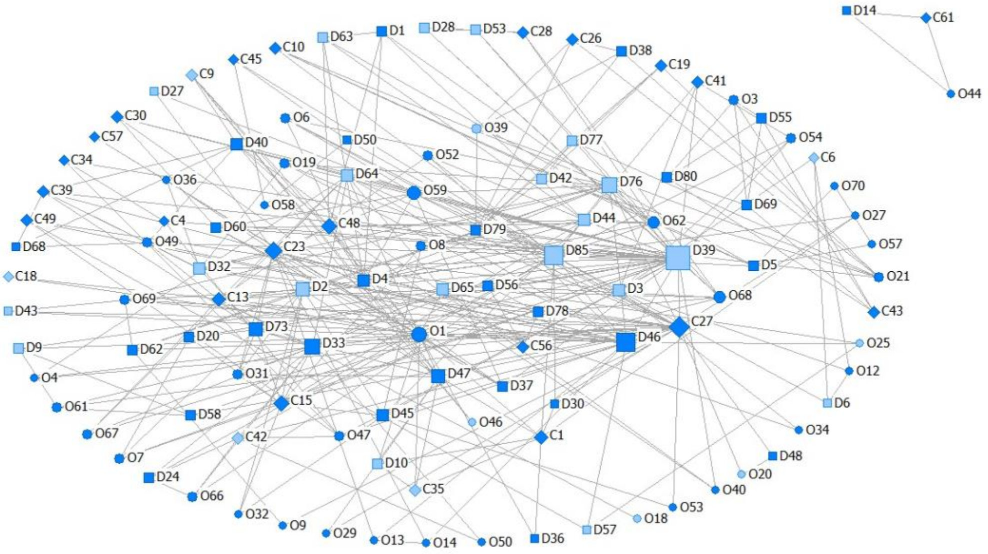
Time Points	Density of linkages		Number of nodes in the core	Final fitness
	Core	Periphery		
2013				
Core	0.600	0.091	11	0.40
Periphery	0.091	0.100		
2015				
Core	0.468	0.121	15	0.391
Periphery	0.121	0.074		
2017				
Core	0.399	0.118	23	0.455
Periphery	0.118	0.034		

4.3.3 Results of Descriptive Analysis on Network Structure of OPCN

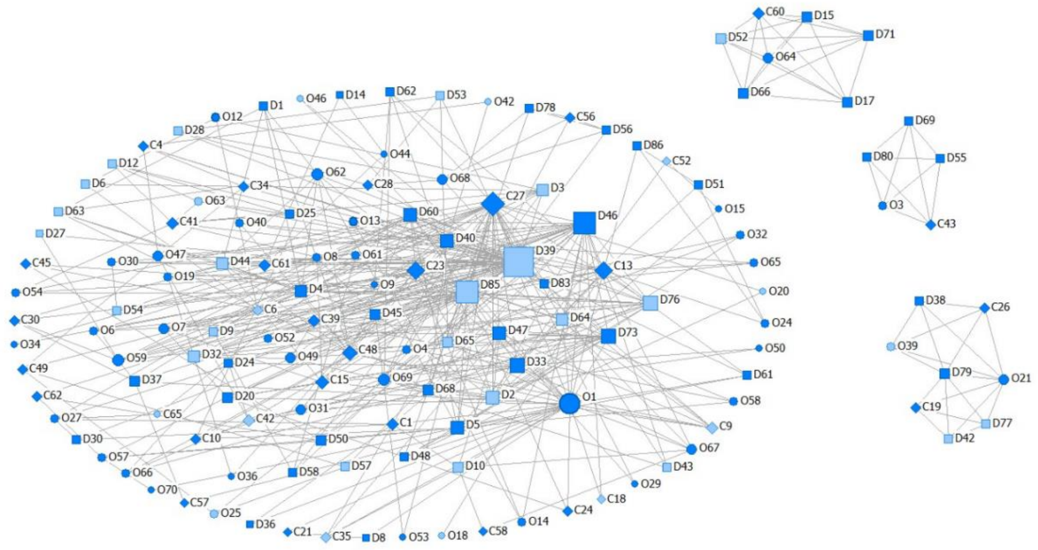
With respect to the OPCN, the same analysis procedures are implemented to investigate the dynamic evolution of network structure during the examined period. Figure 10 has demonstrated that while the network still existed with some independent collaboration in 2017, the network as a whole is trending toward cohesion, where some organizations, including local and overseas designers, local owners, and main contractors, maintain a relatively central position over time.



(a) network structure in 2013



(b) network structure in 2015



(c) network structure in 2017

Figure 10: Evolution of network structure of OPCN

This phenomenon also can be proved by the analysis result as shown in Table 11. The network density, average node degree, and linked node fraction have increased during the examined time. While the main components fraction value in 2017 was almost twice that in 2013, the average geodesic distance was maintained around 2.624-2.724 and slightly decreased over time. These findings indicate that the collaboration in OPCN became closer and the communication in the network became more efficient in 2017 compared with the beginning in 2013. The high main components fraction and low average geodesic distance together show small-world features in OPCN with a quick travel of information among organizations around the core nodes in the network.

The core-periphery analysis is conducted to further explore the evolution of network structure, as shown in Table 12. With the decreasing clustering coefficient presented in Table 11, the percentage of nodes in the core also shows a downward trend during the examined period. Such small-world characteristics make it possible for the organization involved in the network to get connected with each other in a small number of steps.

Table 11 Evolution of network structure for OPCN: Descriptive analysis results

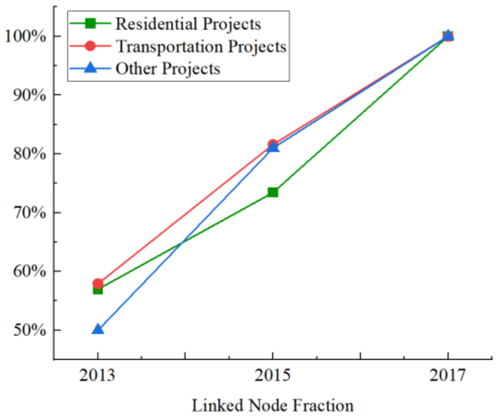
Indicator	2013	2015	2017
Nodes Number	71	115	142
Liked tie number	356	682	902
Network Density	0.072	0.052	0.045
Average Node Degree	5.104	5.930	6.352
Linked-node Fraction	0.500	0.810	1.000
Main-components Fraction	0.458	0.697	0.859
Avg Geodesic Distance	2.724	2.602	2.625
Clustering Coefficient	0.827	0.796	0.792
Deg Centralization	0.235	0.277	0.285

Table 12 Core-periphery structure in OPCN

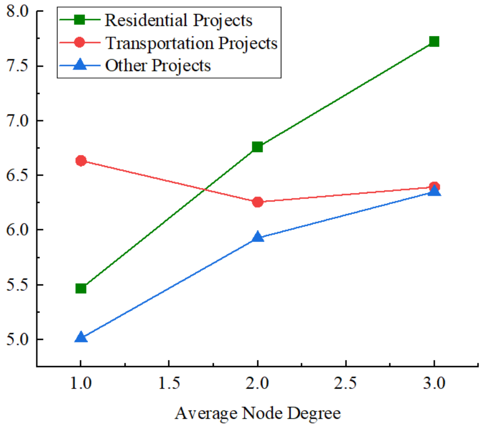
Time Points	Density of linkages		Number of nodes in the core	Final fit
	Core	Periphery		
2013				
Core	0.366	0.085	18	0.414
Periphery	0.085	0.030		
2015				
Core	0.053	0.075	22	0.359
Periphery	0.075	0.025		
2017				
Core	0.370	0.066	25	0.374
Periphery	0.066	0.022		

4.3.4 Result of the Comparative Analysis of Network Structure Among RPCN, TPCN and OPCN

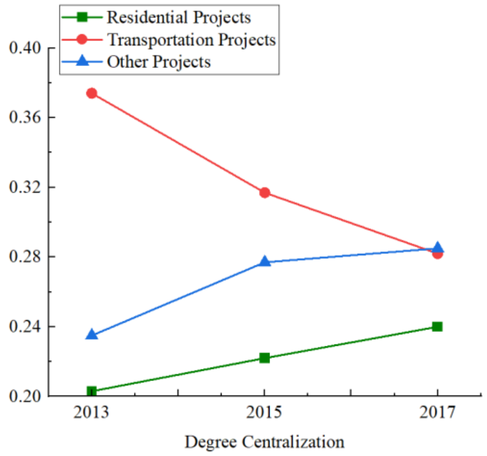
To further explore the difference in collaborative networks among the RPCN, TPCN, and OPCN, the comparison analysis result has been demonstrated in Figure 11. As illustrated in Figure 11 (a), the average node degree of RPCN and OPCN has been increased with a more pronounced increase in RPCN. The result indicates that the node in RPCN has more direct connections among each other, where each node connected with almost eight others on average in 2018. Although the average node degree of TPCN has slightly decreased over time, the values have remained stable at 6.258-6.636. The results illustrate that residential projects are generally more complex and require the involvement of a broader range of organizations.In contrast, transport projects have been more stable in terms of participants. With respect to the linked node fraction, although all three networks reached 100% in 2017, there is a significant difference in the growth rate. The value of RPCN and TPCN is higher than OPCN in 2013. However, while the growth of TPCN has been significantly shown in Figure 11 (a), the speed of growth in RPCN is relatively slow during the examined year. Compared with the transportation project and the other projects, the analysis result has provided clear evidence that the collaborative network in the residential project is established slower. Figures 11 (c) and (d) have provided the comparison result of the clustering coefficient and main-components fraction. Although the clustering coefficient value of all three networks has been significantly decreased over time, the RPCN showed the lowest value in 2018. In contrast, the overall tendency of the main components fraction is growing during the examined period, where the main components fraction of RPCN reached the highest values among the three types of collaborative networks. As for the degree centralization, it is plotted in Figure 11 (e) that there is a significant decrease in the TPCN, while the increment of RPCN and OPCN are similar. Specifically, the value of RPCN remained the lowest during the investigated period and reached 0.24 in 2017, while the value of TPCN and OPCN both settled at 0.28 in 2017.



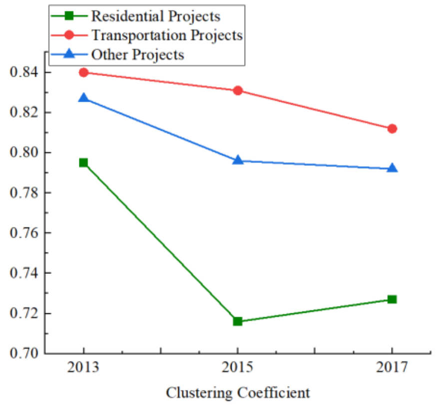
(a)



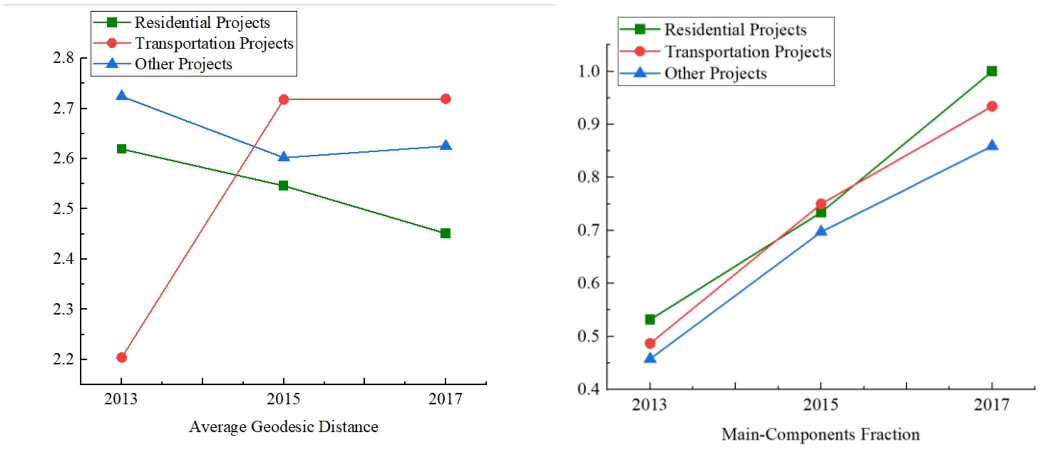
(b)



(c)



(d)



(e) (f)

Figure 11 Comparisons of the evolution of network indicators among RPCN, TPCN, and OPCN

In addition to the difference among network characteristics, the prominent nodes of the individual network and its evolution over the examined period also exist differently. Table 13 presents the five top-ranked core organizations of different time slots in the RPCN, TPCN, and OPCN. It is evident that the core participating organizations of RPCN and TPCN mainly consist of local owners and both local and overseas design consultants. Meanwhile, the organizations involved in the other projects are more complicated, and there exists an obvious replacement of core nodes. Moreover, it is both represented in Table 13, Figure 8 (c), and Figure 9 (c), the most prominent nodes of RPCN and TPCN are occupied by O27 and O47, respectively, throughout the examined period.

Table 13 Five-top ranked core organizations in the RPCN, TPCN, and OPCN during 2008-2017

Year	Residential Project	Transportation Project	Other types of Projects
2013	O27 D2 D3 D39 D67	O47 D76 D3 D85 D67	D46 D47 C27 D39 D47
2015	D27 D85 D76 D48 D60	O47 D3 D39 D2 D76	D39 D46 D85 C27 D76
2017	O27 D68 D2 D29 D5	O47 D39 D3 D2 D10	D39 D46 O1 D85 C27

4.4 Discussions and Implications

This section aims to use longitude data on BIM-based construction projects in Hong Kong to classify the BIM-based construction projects by type and quantitatively characterize and compare the evolution of collaboration networks.

The descriptive analysis results have provided clear evidence that the tendency of the collaborative network of all the three kinds of construction projects became density during the examined time. However, all the three networks (RPCN, TPCN, and OPCN) are persistently characterized by the short geodesic distance and high clustering coefficient. Together with the topology of RPCN, TPCN, and OPCN plotted in Figure 8 to Figure 10, the results also revealed that the network exhibited a core-periphery structure and extended around a small number of hyperconnected nodes. The findings of the comparative analysis result also indicated that, compared with residential projects, the collaboration relationship of the transportation and other projects tends to be established more quickly. This result also indicates a pronounced tendency for the participants in residential projects to become more complicated over time. This could be explained by the characteristics of regional construction that the BIM-based residential project is mainly public housing projects led by the government with relatively fixed participants in the early period. Later on, due to the increased number of BIM-based residential projects, including both public and private projects, the completion of residential projects often requires the involvement of a more diverse organization. With respect to characterizing the roles of core organizations in the evolution of the three networks, the result also reveals that the local owners which consistently occupied a central position in the RPCN throughout the examined period, the design consult including both local and overseas companies, gradually performance actively in the network. Similarly, the key organization during the evolution process of TPCN is the local owner, whereas only the overseas company contributes more actively in the later network.

In contrast, the top-ranked core organization in the OPCN during 2008-2017 is local design consults. The result also indicates that OPCN has a more diverse composition of key organizations than RPCN and TPCN, with more active contributions from local main contractors in the later collaborative networks. This could probably be explained by the influence of government initiatives in promoting BIM in public housing and metro projects. Meanwhile, the efforts of large local owners to facilitate the implementation of BIM are also the primary causes of the differences in BIM-based projects in the regional construction industry. For example, the prominent node in the RPCN and TPCN is the Housing Department and MTR Corporation Limited, respectively. Taken together, this section proved that there are differences in the implementation of BIM in different types of projects, not only including the main participants but also reflected in the evolution process and complexity of the collaborative network.

In conclusion, this result has provided the dynamic evolution of collaboration networks in terms of BIM implementation practice in different projects. The results of the study also provide a reference for differentiated management of construction projects from the perspective of project types and further promote the proliferation of innovative technologies such as BIM within the construction industry.

4.5 Chapter Summary

This chapter first collected the longitudinal data on BIM-based construction projects undertaken in Hong Kong during 2008-2017 through a questionnaire survey, web crawler, and semi-structured interview. Using the network perspective, this chapter has categorized the BIM-based project collaborative network by project type into residential project collaborative network, transportation project collaborative network, and the other project collaborative network. This chapter also modeled and compared the dynamic evolution of the aforementioned three kinds of collaborative networks for BIM implementation over time. As all the three types of collaborative networks become denser over time, proved by the social network analysis result, the collaborative network consistently exhibits a core-periphery structure with a tendency to expand around a small number of “super” connected nodes.

In conclusion, this chapter not only provides a classification method of BIM collaboration networks based on project types but also analyzes the evolution process of collaborative networks of different project types from a network perspective. The findings of this chapter also have provided several managerial and policy implications.

CHAPTER 5 Modeling the Dynamics of Project-Based Collaborative Networks for BIM Implementation

5.1 Introduction

As consistent research of section 4, this section aims to further characterize and explore how and why the macrostructure of the project-based collaborative network for BIM implementation in the Hong Kong construction industry evolves over time. Using the stochastic actor-oriented models (SAOM) method (Snijders et al., 2010) and longitudinal data on BIM-based construction projects undertaken during 2008-2017, the collaborative relationships within the industry-level network examined in this section are limited to inter-organizational ties for collaborative BIM implementation in construction projects. The relationships among the three following types of organizations are specifically investigated in this study due to their critical roles in project-level BIM implementation processes (D. Cao et al., 2015): owners, design consultants and main contractors. Based on the network dynamics models embedded in the SAOM method (Snijders et al., 2010) and taking into account the characteristics of project-based collaborative networks in the construction industry, both endogenous and exogenous effects are examined in this study to characterize how and why the project-based collaborative network evolves over time. The endogenous effect characterizes how the changes of network ties are determined by the network structure itself, whereas the exogenous effects characterize how the changes of network ties are determined by the attributes of network nodes (Snijders et al., 2010). The remainder of this chapter will first propose the research hypotheses on the influences of different effects, then uses the SAOM method and the data set to conduct the network analysis.

5.2 Theoretical Background and Research Hypotheses

5.2.1 Effect of Preferential Attachment in the Dynamics of Project-based Relationship Networks

The preferential attachment effect refers to the rich-get-richer tendency underlying the dynamics of networks. It reflects that those “central” nodes that have already been connected to a large number of other nodes in a network will receive more new connections and thus become more central in the network over time (Barabási & Albert, 1999). Although the deployment of BIM in Hong Kong could date back to about a decade ago, the diffusion of the technology is still not widespread, and many organizations are still sitting on the sidelines of BIM adoption at present. Due to the complexity of the BIM technology (Eastman et al., 2011) and the importance of project-based learning for organizations in the construction industry (D. Cao et al., 2018), design consultants and main contractors that have previously collaborated with other organizations in BIM-based projects are likely to be more advantageous in building their BIM capability and thus be more favored by owners in new BIM-based construction projects. Moreover, previous project-based collaborative linkages can further act as “prisms” and signaling channels of the market status and organizational capability, which can also help those “central” organizations (i.e., have more connections with other organizations) to obtain more new project contracts and establish more new project-based collaborative linkages (D. Cao et al., 2018). Therefore, while (D. Cao et al., 2017) has validated the significance of the preferential attachment effect in the dynamics of collaborative network for BIM implementation in the region of Shanghai, this study proposes that the similar rich-get-richer tendency also applies in the network in Hong Kong. These discussions lead to the following hypothesis:

Hypothesis 1: In a project-based collaborative network for BIM implementation, design consultants and main contractors with more prominent network status (i.e., have more project-based collaborative linkages with other organizations) will be more favored by owners in new BIM-based construction projects and thus more likely to obtain new project-based collaborative linkages over time.

5.2.2 Effects of Organization Type Similarity and Experience Similarity in the Dynamics of Project-based Relationship Networks

Another potential effect underpinning the dynamics of project-based collaborative networks for BIM implementation is that organizations may tend to collaborate more frequently with other organizations with similar attributes. This effect is called the similarity effect (Hanaki et al., 2010; Snijders et al., 2010) or the homophily mechanism (McPherson et al. 2001). Several empirical studies in other domains have validated this effect in the dynamics of relationship networks (Lewis, Gonzalez, & Kaufman, 2012; McPherson, Smith-Lovin, & Cook, 2001; Tang et al., 2018). An important organizational attribute closely related to this effect in the dynamics of project-based collaborative networks for BIM implementation in Hong Kong is organizational ownership type (i.e., local or overseas). Studies in other domains suggest that organizations from similar cultural and institutional backgrounds have less coordination costs and are more likely to establish collaborative relationships with each other (Balland, 2012). Although the construction industry in Hong Kong is a relatively open market and has not established legal or institutional restrictions on the entry of foreign firms (Chiang, Tang, & Leung, 2001), the cultural and institutional differences between local and foreign organizations may still result in extra inter-organizational coordination costs. This may increase the possibility of owners selecting design consultants and main contractors with similar ownership types as project partners. Apart from ownership type, organizational BIM experience is another organizational attribute that might be closely related to the similarity effect underlying the dynamics of project-based collaborative networks for BIM implementation. At present, the advancement of BIM in Hong Kong is still at a relatively preliminary stage, and there are only a limited number of experienced design consultants and main contractors in the industry. Due to the influence of BIM experience on the success of project-level BIM implementation practices, these experienced design consultants and main contractors might become relatively popular in the market and thus be successfully pursued primarily by those advantageous owners which are also experienced BIM users. This could result in the experience-related homophily tendency in the project-based collaborative networks for BIM implementation in the industry. Based on these considerations, the following set of hypotheses on the similarity effect are proposed.

Hypothesis 2: In a project-based collaborative network for BIM implementation, project owners are more likely to establish collaborative relationships with design consultants and main contractors that have similar organizational ownership types.

Hypothesis 3: In a project-based collaborative network for BIM implementation, project owners are more likely to establish collaborative relationships with design consultants and main contractors with similar BIM experience.

5.3 Research Method

5.3.1 Longitudinal Data and Descriptive Network Indicators

This longitudinal data on BIM-based construction projects conducted in Hong Kong during the past decade (2008-2017) data collected in section 4.2.1 was continued to be used in this section. The social network analysis was first conducted to investigate the evolution of network characteristics for BIM implementation. Then the stochastic actor-oriented models (SAOM) analysis was conducted to test the proposed hypotheses. The demographic information of 192 BIM-based projects and the participated organizations in the BIM implementation practice is demonstrated in Table 14.

Table 14 Demographic information

Variable	Category	Number	Percentage
Project size	Below HK$200 million	16	9.04%
	HK$200-2000 million	95	53.67%
	HK$2000-5000 million	45	25.42%
	Above HK$5000 million	21	11.86%
Project investment nature	Public sector owned	103	58.19%
	Private sector owned	74	41.81%
Project commencement year	2008	6	7.79%
	2009	5	6.49%
	2010	8	10.39%
	2011	17	22.08%
	2012	11	14.29%
	2013	30	38.96%
	2014	22	28.57%
	2015	27	35.06%
	2016	27	35.06%
	2017	24	31.17%
Role of project participating organizations	Owner	64	31.37%
	Design consultant	80	39.22%
	Main contractor	60	29.41%

The ownership type of owners	Local	58	28.43%
	Overseas	6	2.94%
The ownership type of design consultant	Local	50	24.51%
	Oversea	30	14.71%
The ownership type of the main contractor	Local	39	19.12%
	Foreign	21	10.29%

Following the rules in section 4.2.1, the same one-mode matrice was transformed from the original data. Specifically, to be consistent with the data processing requirements for the analysis based on the method of SAOM (Snijders et al., 2010), all the values r_{ij} in these two types of matrices were dichotomized for subsequent network analysis.

As previously indicated, SAOM is the principal network analysis method used in this study. Before using SAOM to test the proposed hypotheses on the dynamics of project-based collaborative networks for BIM implementation, a descriptive network analysis was first conducted to characterize the structures of project-based collaborative networks for BIM implementation in the Hong Kong construction industry during different times frames. In addition to the indicator listed in Table 6, the additional two descriptive network indicators, which are specifically used to describe the overall network characteristics, are listed as follows:

(1) Average distance among main-component nodes: The average distance among main-component nodes refers to the average of the geodesic distances between the nodes in the main component.

(2) Freeman's graph centralization: The Freeman's graph centralization measures the degree of inequality or variance in a network as a percentage of that in a perfect star network (Freeman, 1978). The centralization indicator used in this study is based on

the degree centrality of network nodes. The values of this indicator range from 0 to 1, with values closer to 1 indicating higher levels of centralization.

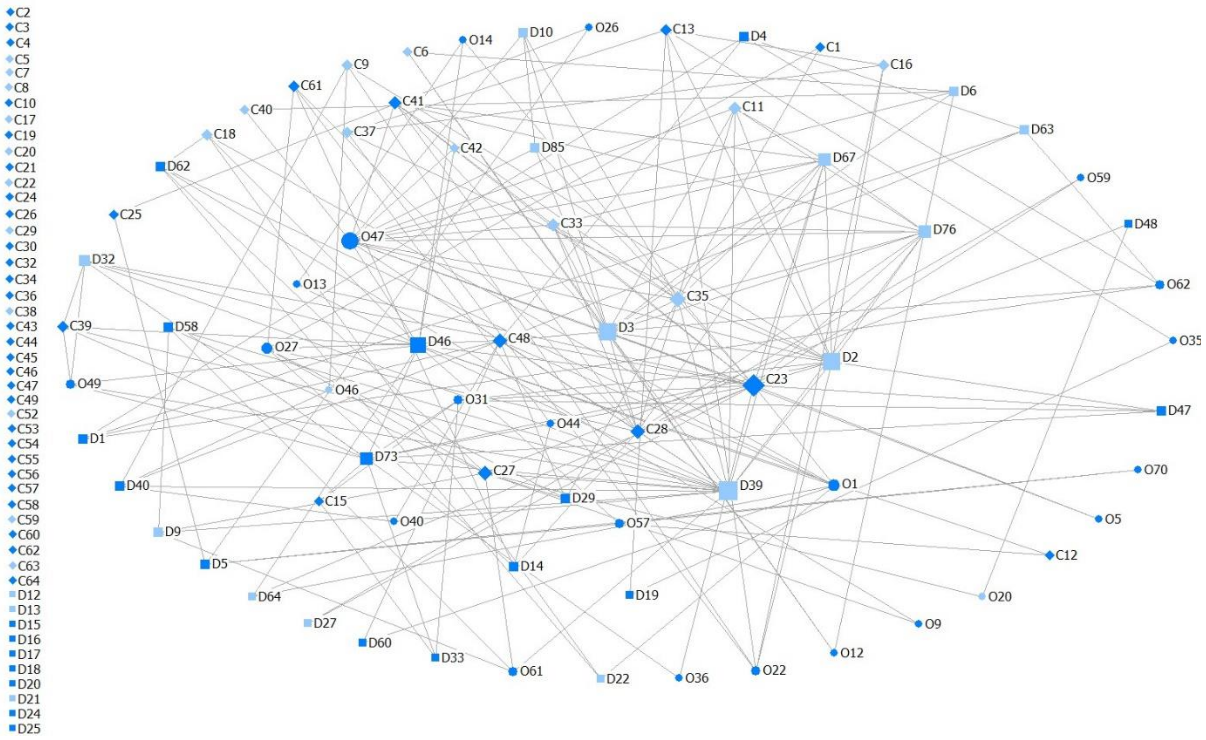
5.3.3 Stochastic Actor-Oriented Models (SAOM)

Related to the three proposed hypotheses, the following effects driving network dynamics were principally investigated in this study: the *preferential attachment effect* related to network structures, the *similarity effect* related to organizational ownership type, and the *similarity effects* related to organizational BIM experience. With regard to H1, specifically, the *preferential attachment effect* was specifically examined through assessing whether the design consultants and main contractors with more prominent network positions (i.e., with higher in-degrees) in a collaborative network for BIM implementation will be more frequently selected by owners in new BIM-based construction projects and thus gain more new collaborative ties over time (Snijders et al., 2010). With regard to the *similarity effects* used to test H2 and H3, the *same covariate effect* was specifically examined to assess whether project owners are more likely to establish collaborative relationships with design consultants and main contractors that have similar organizational ownership types or BIM experience. Consistently, organizational ownership type and BIM experience were both set as dummy variables to reflect whether the examined organization is local organization in Hong Kong or not (1 = local; 0 = overseas) and has project-level BIM implementation experience before December 31st 2012 (i.e., mid of 2008-2017) or not (1 = have; 0 = do not have). To better assess the incremental influences of these effects, this study also controlled for the individual covariate effects of these two variables when examining the dynamics of project-based collaborative networks. These were examined through the covariate-ego effect and the covariate-alter effect, with the former examining the influence of the attributes of egos (i.e., owners as tie senders) and the latter examining the influence of the attributes of alters (i.e., design consultants or main contractors as tie receivers).

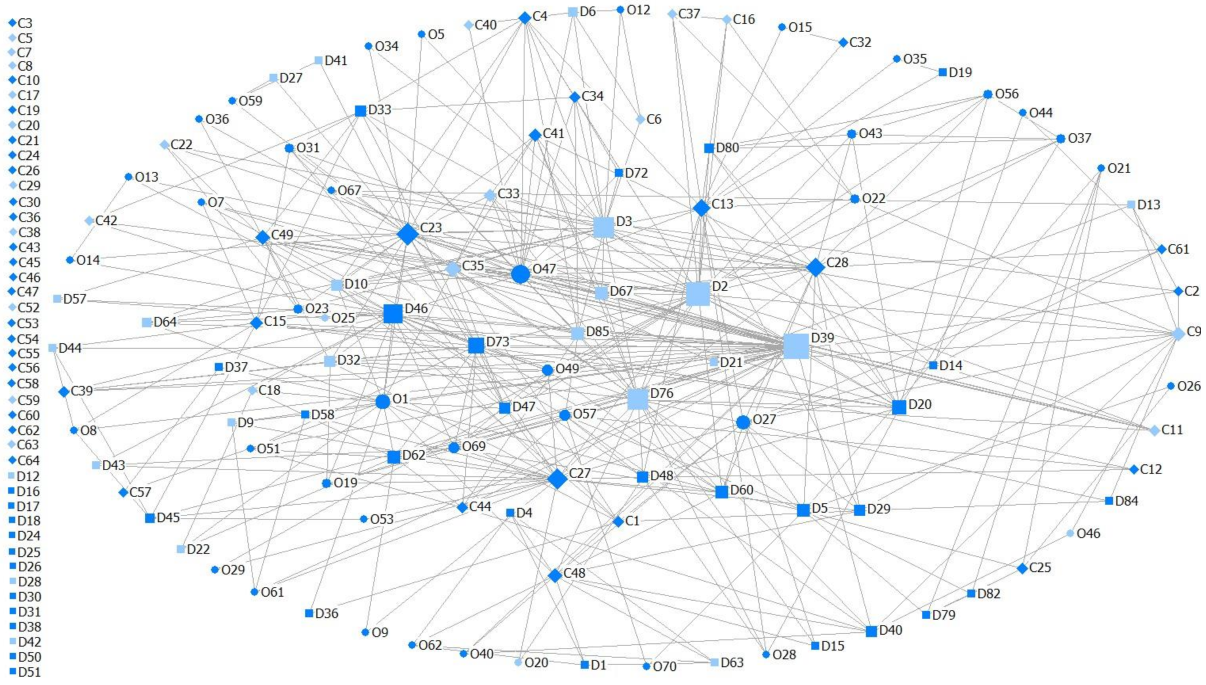
5.4 Data Analysis Results

5.4.1 Results of Descriptive Analysis on Network Structure

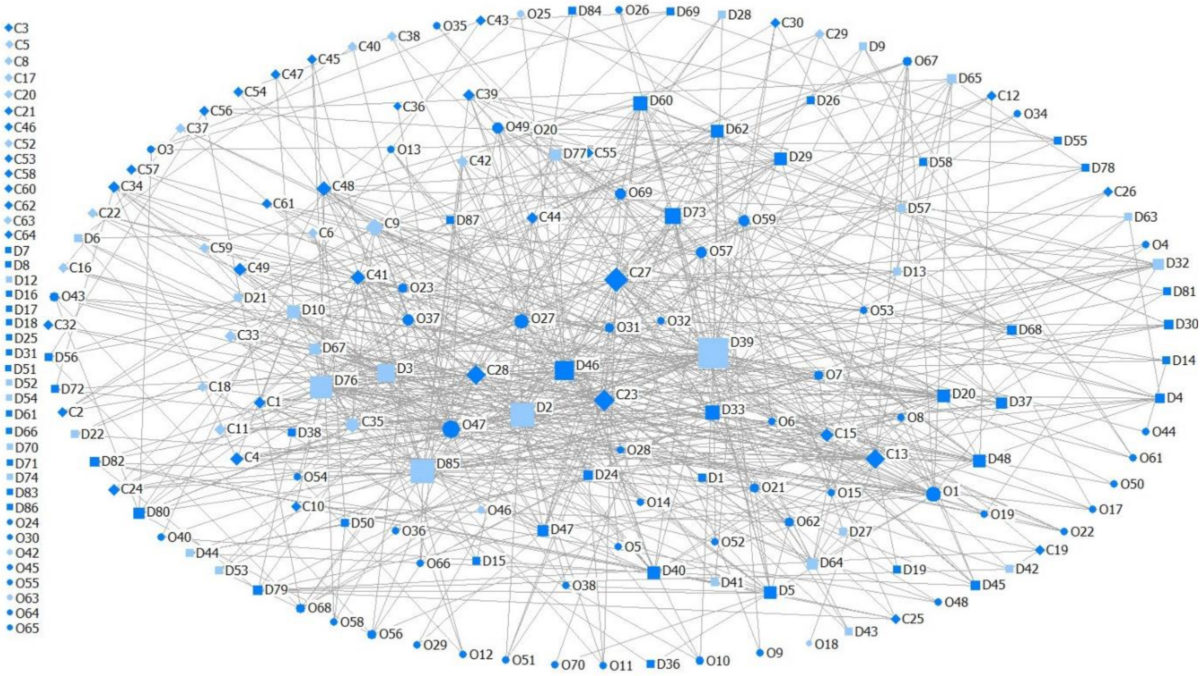
To be consistent with the setting required for subsequent SAOM analysis (Snijders, 2001), this chapter aggregated the data on collaborative relationships before different observed time points to construct project-based collaborative networks. Specifically, the collaborative networks based on BIM-based projects during 2008-2017 were observed at four times: 2011, 2013, 2015, and 2017, with each network only covering the inter-organizational collaborative relationships which were formed in the projects, started before or in the observed year. In this section, the year 2011 was set as the first examined time point. Based on the UCINET 6.636 and its visualization package NetDraw, the dynamic collaborative network up to the four observed years (namely 2011, 2013, 2015, and 2017) are illustrated in Figure 12. The representation of node shapes and color are consistent with that in Section 4.3.



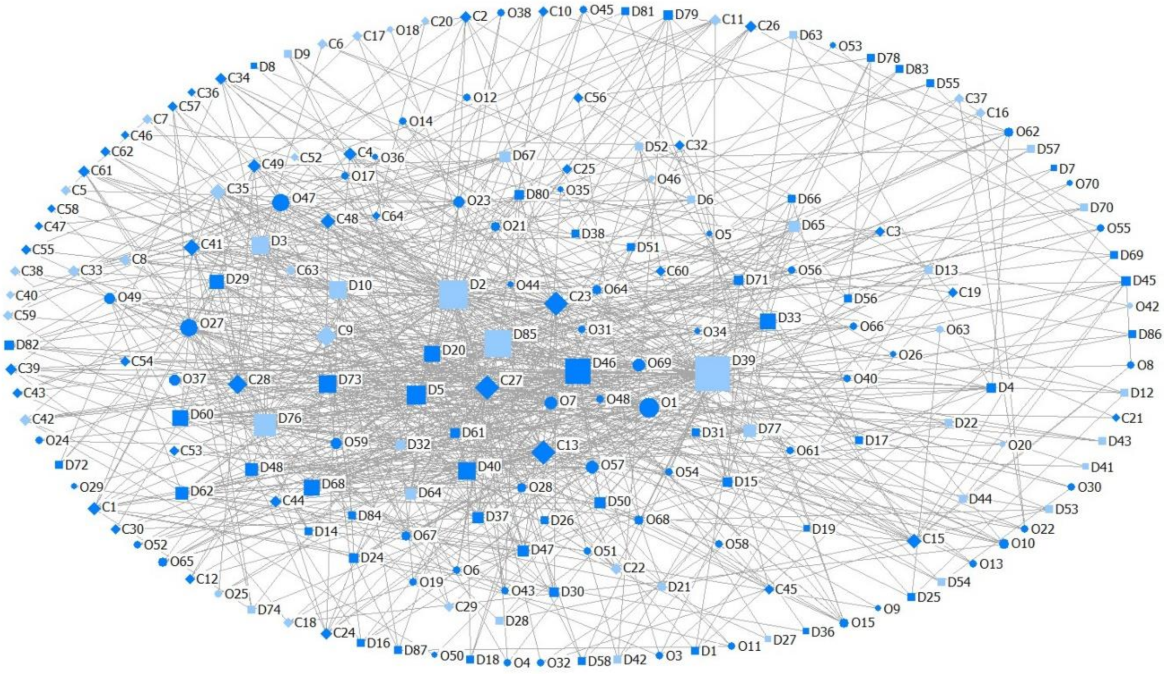
(a) Network structure in 2011



(b) Network structure in 2013



(c) Network structure in 2015



(d) Network structure in 2017

Figure 12 Evolution of network structure

It is evident from Figure 12 that the collaborative network generally becomes denser over time and that there are some organizations, including not only local owners but also overseas design consultants and local main contractors, continuously occupying relatively central positions in the network throughout the examined period. A set of statistics reflecting the changes of the network structure were further calculated and are reported in Table 15. As illustrated in Table 15, the network density, the average node degree and the linked node fraction have all obviously increased during the examined period, with the value of the average node degree in 2017 becoming three times higher than that in 2011. This result reflects that an increased number of organizations have started to implement BIM during the past decade and that the organizations involved in BIM implementation in early periods have played important roles in facilitating the diffusion of BIM in the regional construction industry.

Table 15 Evolution of network structure: dscriptive analysis results

Indicator	2011	2013	2015	2017
Network density	0.010	0.020	0.032	0.043
Average node degree	2.020	4.118	6.559	8.765
Linked node fraction	0.130	0.317	0.638	1.000
Main-component fraction	0.363	0.564	0.799	1.000
Average distance among main-component nodes	2.986	2.717	2.672	2.682
Clustering coefficient	1.784	1.333	1. 215	1.123
Freeman's graph centralization	0.099	0.159	0.251	0.290

It is also illustrated in Table 15 that although the main component fraction has increased nearly three times during the whole examined period, the average distance among main-component nodes has not changed obviously but kept around 2.682-

2.986. These distance values indicate each organization reaches any other organization in the main component of the network through a path of less than 3 steps on average. These values are relatively small and close to the average distances of random graphs with the same number of linked nodes (the average distance values of the random graphs equivalent to the main components in 2011, 2013, 2015, and 2017 are 2.507, 2.387, 2.420, and 2.450 respectively). With regard to the clustering coefficient, its value has continuously decreased during the examined period but kept substantially larger than the clustering coefficients of random graphs with the same number of linked nodes after 2011 (the clustering coefficients of the random graphs equivalent to the networks in 2013, 2015 and 2017 are 0.137, 0.122 and 0.114 respectively). As suggested by Watts and Strogatz (1998), the short average distance among network nodes and high clustering coefficient indicates that the investigated project-based collaborative network for BIM implementation persistently exhibits small-world properties.

Despite the continuous decrease of the clustering coefficient, as shown in Table 15, the Freeman's graph centralization of the network steadily increased from 0.099 in 2011 to 0.290 in 2017. This result provides evidence that the project-based collaborative network for BIM implementation in Hong Kong has shown a tendency to develop around a small number of “star” organizations during the past decade, which could also be visually observed from the network structures depicted in Figure 12. Core-periphery structure analysis based on the algorithm proposed by Borgatti and Everett (2000) were further conducted to quantitatively assess this tendency. As shown in Table 16, the analysis results provide evidence that the collaborative network has persistently exhibited the core-periphery structure during the examined period. It is shown that the super-connected nodes in the core only account for a small proportion of the network size, whereas a large majority of the investigated organizations are sparsely connected nodes located in the periphery. Further analysis on the cumulative distribution of node degrees at the time of 2017 also shows that, as depicted in the double logarithmic coordinate system in Figure 13, the distribution evidently exhibits power-law scaling which has the approximate fit $P(K) \sim 3.586 \times K^{-1.246}$. This result suggests the "scale-free" characteristic of the investigated collaborative network (Barabási & Albert, 1999). Taken together, these results provide clear evidence for the uneven distribution of project-based collaborative ties for BIM implementation among industry organizations during the investigated period.

Table 16 Core-periphery structure in the collaborative network

Time Points	Density of linkages		Number of nodes in the core	Final fit
	Core	Periphery		
2011				
Core	0.833	0.022	12	0.540
Periphery	0.022	0.006		
2013				
Core	0.374	0.033	29	0.464
Periphery	0.033	0.007		
2015				
Core	0.363	0.051	36	0.466
Periphery	0.051	0.009		
2017				
Core	0.472	0.078	32	0.472
Periphery	0.078	0.016		

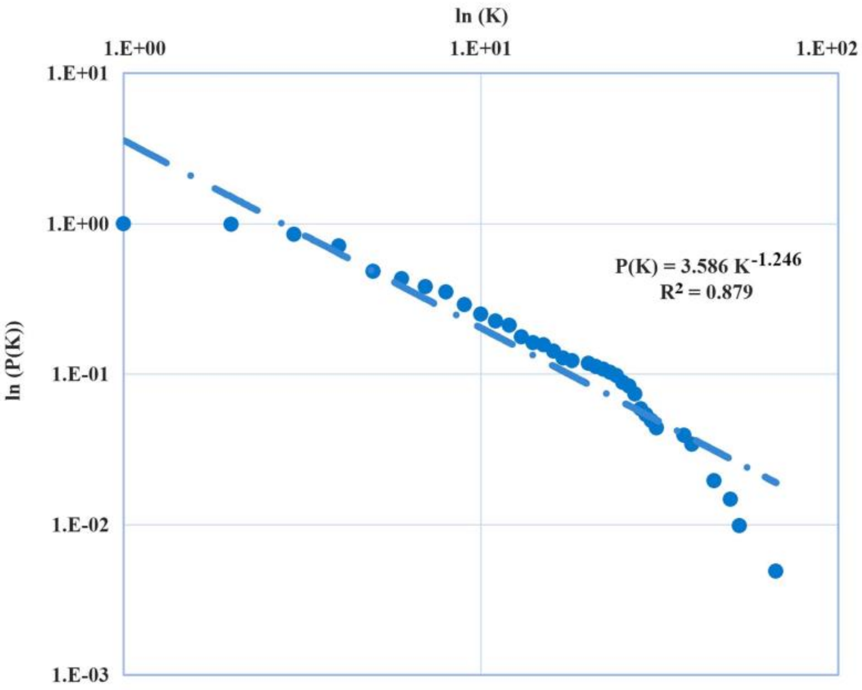


Figure 13 Power-law distribution of node degrees in 2017

5.4.2 Results of SAOM Analysis on Effects Underlying Network Dynamics

The proposed hypotheses on the effects underlying the dynamics of project-based collaborative networks for BIM implementation were tested using the SAOM analysis, which was implemented in the program *RSiena 1.1-290* (Ripley et al., 2011). Since the formation of the project-based collaborative relationships for BIM implementation among owners, design consultants and main contractors is determined by how owners choose project partners, the matrices reflecting the project-based collaborative ties from owners to design consultants and main contractors were used as the input data to analyze the dynamics of project-based collaborative networks for BIM implementation (D. Cao et al., 2017), with the ties from designers or general contractors all being set as structural zeros. Consistent with the data set for the SAOM method (Snijders, 2001), this study aggregated the data on collaborative ties before and in corresponding observed time points (namely the years 2011, 2013, 2015 and 2017) to construct the matrices. The default parameter estimation procedure based on the method of moments was used for the SAOM analysis (Snijders, 2001). The model estimation results, which are based on 3330 estimation iterations, are demonstrated in Table 17. The *overall maximum convergence ratio* (0.1304) is smaller than the suggested criteria of 0.25, and the *t statistics for deviations from targets* of the estimated parameters are all below the threshold of 0.1, suggesting satisfactory convergence of the estimation results (Ripley et al., 2011).

Table 17 Effects underpinning network evolution: SAOM analysis results

Independent Variables	Estimate	Standard error	t-ratio	t-value
Rate Parameters				
Rate parameter for period 1 (2011-2013)	1.698	0.178	N/A	9.542
Rate parameter for period 2 (2013-2015)	1.943	0.184	N/A	10.577
Rate parameter for period 3 (2015-2017)	1.643	0.167	N/A	9.832
Structure-based preferential attachment effect				
In-degree popularity	0.164	0.018	-0.032	9.318
Attribute-based similarity effects				
Organization type similarity	0.174	0.341	0.027	0.512
BIM experience similarity	0.250	0.121	-0.014	2.071
Controls: covariate-ego and covariate-alter effects				
Organizational ownership type of alter	0.255	0.347	0.041	0.736
Organizational ownership type of ego	15.071	1.861	0.005	8.099
BIM experience of alter	0.308	0.150	-0.060	2.062
BIM experience of ego	13.021	2.268	0.085	5.741

The rate parameters in SAOM models reflect the expected frequencies with which network nodes get the opportunity to change a collaborative tie during corresponding periods. As shown in Table 11, the rate parameters for the three periods between the four observed time points are between 1.643-1.943 and all are statistically significant ($p < 0.001$). This result provides evidence for the substantial and steady increase in newly-formed collaborative relationships for BIM implementation among industry organizations throughout 2011-2017. With regard to the tested hypotheses, Hypothesis 1 is about the *preferential attachment effect*, which reflects whether the design consultants and main contractors with more prominent network positions in a collaborative network for BIM implementation will be more frequently selected by owners in new BIM-based construction projects and thus gain more new collaborative ties over time. This effect was specifically examined using the in-degree popularity effect within *RSiena*. As shown in Table 17, the unstandardized coefficient for this effect is positive and highly significant (β=0.164, $p < 0.001$). Therefore, Hypothesis 1 is empirically supported. Hypotheses 2 and 3 are about attribute-based similarity effects, which reflect whether project owners are more likely to establish collaborative relationships with design consultants and main contractors that have similar organizational ownership types and BIM experience. These were specifically examined using the same covariate effect within *RSiena*. As shown in Table 17, the estimated coefficient for the similarity effect related to organizational ownership type is positive but not statistically significant ($\beta = 0.174$, $p > 0.05$), whereas the coefficient for the similarity effect related to BIM experience is positive and significant at the 5% level ($\beta = 0.250$, $p < 0.05$). Therefore, Hypothesis 3 is empirically supported, while Hypothesis 2 is not.

The four control effects are about the individual covariate effects related to the variables of organizational ownership type (i.e., local or overseas) and organizational BIM experience, which reflect how the attributes of egos (i.e., owners as tie senders) or alters (i.e., design consultants or main contractors as tie receivers) separately influence the formation of project-based collaborative networks for BIM implementation. These were examined through the covariate-ego effect (egoX) and the covariate-alter effect (alterX) within *RSiena*. With regard to the individual covariate effect related to organizational ownership type, it is evident from Table 17 that the effect of egos' organization type is highly significant (β = 15.071, $p < 0.001$) but the effect of alters' organization type is not statically significant (β = 0.255, $p > 0.05$). With regard to the individual covariate effect related to organizational BIM experience, it is shown in Table 17 that the covariate-alter effect (β = 0.308, $p < 0.05$) and the covariate-ego effect (β = 13.021, $p < 0.001$) are both statistically significant. Together with the analysis results of the same covariate effects related to Hypotheses 2 and 3, this result tends to suggest that compared with organizational ownership type, organizational BIM experience generally plays a more important role in impacting the formation of project-based collaborative relationships for BIM implementation in the Hong Kong construction industry.

5.5 Discussions and Implications

The objective of this chapter is to use longitude data on BIM-based construction projects in Hong Kong to quantitatively characterize how and why the macrostructure of project-based collaborative networks for BIM implementation in the construction industry evolves over time. The results of descriptive network analysis reveal that the collaborative network in Hong Kong becomes increasingly dense over time but is persistently characterized with relatively short path lengths among network nodes and a high clustering coefficient. The results also reveal that the collaborative network persistently exhibits the core-periphery structure and there is a tendency for the network to expand around a small number of “super-connected” nodes. With regard to the micro-mechanisms driving the dynamics of the collaborative network, this study has proposed three research hypotheses on the influences of the preferential attachment effect as well as the similarity effects related to organizational ownership type and organizational BIM experience. The hypotheses on the influences of the preferential attachment effect and the similarity effect related to organizational BIM experience were both validated by the longitudinal data, whereas the influences of the similarity effect related to organizational ownership type are not statistically significant. This result indicates that there is no obvious tendency for project owners to more frequently select design consultants and main contractors that have similar organizational ownership types as project partners in BIM-based projects in Hong Kong. As the vast majority (90.63%) of the owners of the investigated BIM-based projects are local organizations, a plausible explanation for this result is that the development of BIM in Hong Kong is still at a relatively primitive stage and most local designers and contractors (especially design consultants) are generally less advantageous in terms of BIM capability than large overseas firms (i.e., AECOM and Arup) when bidding for new project contracts. Further independent-sample T-test also provides evidence that the BIM experience of local design consultants and main contractors (mean = 0.382) is generally lower than that of foreign counterparts (mean = 0.471), although the difference is not statistically significant (p = 0.309). This result is also largely corroborated by the results of non-significant covariate-alter effect related to organizational ownership type (β = 0.255, $p > 0.05$) and significant covariate-alter effect related to organizational BIM experience (β = 0.308, $p < 0.05$), which similarly indicate that compared with organizational ownership type, BIM experience generally plays a more important role in impacting the possibility of design consultants and main contractors to be selected as project partners by owners in BIM-based construction projects. While previous simulation-based studies suggest that relational instability in project-based collaborative networks could slow inter-organizational learning and thus influence organizational performance (Taylor, Levitt, & Villarroel, 2009), the present study provides further empirical evidence that such a relational instability not only relates to the structure of the relationship networks but is also contingently influenced by the attributes of the collaborative organizations.

Although recent years have witnessed increasing attempts to investigate industry-level collaborative networks in the construction domain, which aggregate collaborative relationships in different projects as project-based macro-networks, most of these investigations primarily focus on using the static network perspective to characterize the structural characteristics (Y.-S. Lee et al., 2016; H. Park et al., 2011) or the performance impacts (D. Cao et al., 2018; Jason West, 2014) of the collaborative networks in specific time periods. By contrast, relatively few studies have been conducted to further characterize how and why these industry-level macro networks evolve over time and thus offer further insights into the complex adaptive systems nature of the relationship networks among firms in the construction industry (Guevara, Salazar, & Garvin, 2020; Han et al., 2018). Based on the SAOM method and a unique longitudinal data set of BIM-based projects in Shanghai D. Cao et al. (2017), represent an exploratory effort in this direction. While the research focus of D. Cao et al. (2017) is also about the evolution of collaborative networks for BIM implementation, the present study, which is based on the longitudinal in Hong Kong, not only re-validates the significance of the preferential attachment effect underlying the dynamics of collaborative networks for BIM implementation in another institutional and cultural context but also further validates the significance of the similarity effect related to organizational BIM experience. Taking into consideration the market characteristics of the Hong Kong construction industry, moreover, the present study has further quantitatively examined the roles of the similarity effect and the individual covariate effects related to organizational ownership type (i.e., local or overseas) underlying the dynamics of project-based collaborative networks for BIM implementation.

Together with the research findings in chapter 4, as such, the present study could contribute to a more generalized and broadened understanding of how the networks of project-based collaborative relationships in the construction industry evolve as complex adaptive systems whose dynamics are driven by a set of structure- and attribute-based effects operating at the micro-level.

5.6 Chapter Summary

Using the SAOM method and longitudinal data on BIM-based construction projects undertaken in Hong Kong during 2008-2017, this section has characterized how and why the macro-structure of the project-based collaborative network for BIM implementation in the regional construction industry evolves over time. The results of descriptive network analysis reveal that the collaborative network becomes increasingly dense over time but is persistently characterized with the relatively short average path length among network nodes and the high clustering coefficient. The results also reveal that the collaborative network persistently exhibits the core-periphery structure and there is a tendency for the network to expand around a small number of “super-connected” nodes. The results of SAOM analysis further provide evidence that the evolution of the macro-level network significantly relates to the structure-based preferential attachment effect and the experience-based similarity effect operating at the micro-level. In conclusion, this section not only provides a network view of how industry organizations interact with each other in BIM implementation practices across projects, but also contributes to a deepened understanding of how the networks of project-based collaborative relationships evolve as complex adaptive systems whose dynamics are driven by a set of structure- and attribute-based effects operating at the micro-level.

CHAPTER 6 Exploring the Role of Dynamic Capabilities and Social Status in Organizational Innovation Strategic Response

6.1 Introduction

With the rapid development of innovative technologies, enterprises must adopt and absorb them to gain and maintain competitiveness (A. K. Lau & Lo, 2019; Prasanna et al., 2019). The critical challenge for adopting new innovative technology is that diverse actors must cooperate and complement each other in supporting the underlying technology or changing institutional framework conditions, as well as developing and adapting to new cooperation models (Vargo, Akaka, & Wieland, 2020). However, firms commonly differ in the strategic response due to the inherent differences in an organization's dynamic capability (Marsh & Stock, 2006) and current social status (Piazza & Castellucci, 2014).

As discussed in Chapter 4 and Chapter 5, unlike many other industries, the construction industry is a specific project-based sector that involves multiple organizations such as owners, design consultants, and main contractors (J. E. Taylor, 2007). Since the construction industry in Hong Kong is a relatively open market (Chiang et al. 2001), the accomplishment of a BIM-based project may rely on the collaboration of organizations with different attribute types and ownership types. According to the market-driven development process of BIM, described by the analysis results in Chapter 4 and Chapter 5, BIM implementation in the Hong Kong construction industry during the past decade persistently exhibits small-world properties in which the local owners, overseas design consultants, and local main contractors are continuously playing an essential role in BIM-based projects. Hence, the regional market currently exists differences among organizations regarding the maturity and depth of the BIM implementation practice. Given the great potential of BIM application and the mandatory policy released in the regional construction industry, the implementation of BIM has become a development trend that requires close cooperation among different stakeholders. However, due to the diverse different attribute types and ownership types of organizations, the acceptance of innovative technology also varies.

The research to date has tended to focus on investigating the impact of different strategies on organizational performance, further assessing the various strategical responses. What remains unclear is how the organizations choose different strategy according to their specific conditions. To address this research gap, the purpose of this section is to explore the role of dynamic capabilities and social status in organizational innovation strategic response in a systemic way.

6.2 Theoretical Background and Research Hypotheses

6.2.1 Exploring the Diversity in Strategic Response to Innovative Technology

While an increasing number of studies have focused on investigating the categories of different strategies, scant studies have been conducted to explore the driving factors of strategic diversity from the organizational level (Jackson, Joshi, & Erhardt, 2003). To better understand the relationship between organizational resources and strategic responses to innovative technology, R. P. Lee and Grewal (2004) theorized three key components, namely magnitude, domain, and speed, and indicated that the strategic response can be categorized according to a combination of these three components. The present chapter contributes to the aforementioned theoretical model by linking several theories with the components.

Response Speed

The response speed is defined as the timeliness of the response. A faster response organization has more opportunities to learn the new technology and obtain a more competitive position (T. Lau, Wong, Chan, & Law, 2001; Powell, 1987; Tortorella, Vergara, Garza-Reyes, & Sawhney, 2020). Given the fact that the timing of entry in innovation implementation is a critical appropriability consideration (Lavie, Lechner, & Singh, 2007), the response speed is also regarded as a vital factor in managing diverse strategic issues, such as entering new markets or responding to competitive threats (Lumpkin & Dess, 2001). In detail, to gain access to strategic resources (P. Hughes & Morgan, 2008) and increased patentability (Encaoua, Guellec, & Martínez, 2006), the firms' decision to attempt to "first" enter the market is called a first-mover/pioneer strategy (Leiberman & Montgomery, 2012). The first-mover often requires a high level of creativity, market information, and technical requirements (Scherer, 2015), where the pioneering strategy enables the organization to preoccupy scarce raw materials and enhance lead times (C.-H. Chang, 2011; Slater & Narver, 1993). However, an increasing number of researchers have pointed that organizations pursuing first-mover applicability may face a high degree of uncertainty regarding technical feasibility and market demand (Chege & Wang, 2020; Kerin, Varadarajan, & Peterson, 1992).

In contrast, interest in the advantage of fast followers has been growing (Ankney & Hidding, 2005). As Hidding and Williams (2003) defined, the immediate followers are the firms that are second, third, or fourth to adopt the innovative technology or enter the market. The advantage of fast followers can be achieved by entering the market during the growth phase (Shankar et al. 1999), with lower R&D costs, workforce training costs, and consumer education costs. (Wunker, 2012). Whereas the first mover and fast followers are considered an active response to the innovative technology in the market, the late entrant strategy is also a common timing strategy (Staykova & Damsgaard, 2015). Some companies may lack the ability to establish innovation-related resources or personnel in a short period or may want to observe the adoption of technology in the industry. In summary, this research will categorize the response speed to innovative technology into the following three items: first mover, fast follower, and late entrant.

Response Domain

Prior research strives to understand the response domain during the decision-making process in organizations (Ford & Gioia, 2000; Snowden & Boone, 2007). Recently, the innovation study has focused more on the diversity across domains of action rather than the organizational settings (Ford, 1996; Hargadon, 2002). As defined by Nelson and Winter (1982), the response domain belongs to the organization's routines, representing “regular and predictable behavioral patterns of firms.” Specifically, routines-based responses typically include an organization's inherent and customary actions in response to new technologies that emerge in the marketplace. Feldman and Pentland (2003) have provided a detailed definition of routines, which are considered to represent “repetitive, recognizable patterns of interdependent actions, carried out by multiple actors.”

In addition to the routine-based response, the stability of an organization's resources also plays a significant role in managerial decision-making. Therefore, the resource-based response view is also adopted to measure the response domain further. Therefore, the resource-based response view is also adopted to measure the response domain further. Similar to the routines-based response, the resources available to an organization are fundamental in determining ‘where’ the organization can respond to innovation (Feldman & Pentland, 2003; M. A. West & Anderson, 1996). Specifically, the use of existing available resources in developing new and improved ways of doing things within the organization determines the level of innovation (Adams, Bessant, & Phelps, 2006).

Due to the unbalanced characteristics of BIM application in the regional construction industry, different organizations tend to formulate response strategies based on their current development level and routine when facing innovative technologies. Overall, the routines-based responses and resource-based responses have provided a foundation for measuring the managerial decision-making domain in this study.

Response Magnitude

The intensity of an organization's response to innovative technology can range from complete ignorance to acceptance of the technology, and this is also called response magnitude (C. Hughes, Swaminathan, & Brooks, 2019; R. P. Lee & Grewal, 2004). The higher the response magnitude of an organization, the more comprehensive action will be taken to adapt to new technology (Phaal & Muller, 2009). Although the concept of response magnitude is widely acknowledged in innovation-related research, how to measure it explicitly still needs to be further explored. This section builds on the concept and further develops and refines response magnitude according to the “formal strategic planning process” and “planning flexibility” (Abubakar, Elrehail, Alatailat, & Elçi, 2019; Langley, 1988).

The objectives of the formal strategic planning process usually consist of setting goals and determining the extent to which the organization formalizes and documents those goals (Poister, 2010). Based on the prior industry interviews and the area-specific characteristics of BIM applications in the regional industry, a formal strategy could include establishing a standard for BIM use, putting forward a firm-level strategic plan for BIM implementation, and setting specific goals for the BIM implementation process.

Different from the formal strategic planning process, flexibility is the extent of consideration given to new and alternative options during strategic planning (Fagerholt, Christiansen, Hvattum, Johnsen, & Vabø, 2010). As conceptualized by Barringer and Bluedorn (1999), planning flexibility “ refers to the capacity of a firm's strategic plan to change as environmental opportunities/threats emerge.”, allowing positive organizational change to the new technology. Compared with large organizations, some small- and medium-sized organizations may lack the ability to establish a complete and formal response strategy due to inadequate internal resources (Brunswicker & Vanhaverbeke, 2015). Similar to the formal strategic planning process criterion in regional construction, the planning flexibility process of

BIM implementation could include training staff, holding internal or external learning, and purchasing related products. In summary, a more detailed measurement of response magnitude is given by introducing the formal strategic planning process and planning flexibility.

Figure 14 illustrates the conceptual model of strategic response and its components. As shown in the figure, various strategy response options can be conducted according to the overlapped response domain, response speed, and response magnitude.

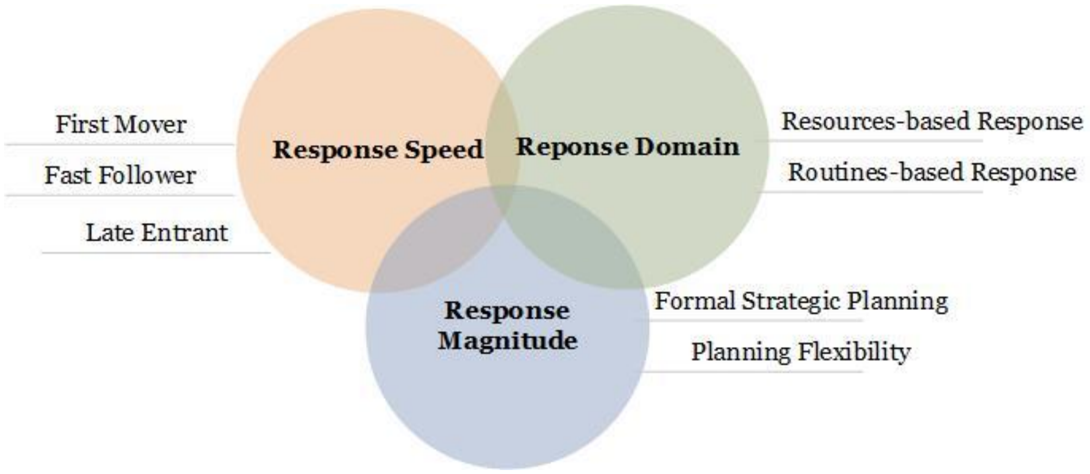


Figure 14 The conceptual model of strategic response

Drawing on the different combinations of response domain, speed and magnitude, and considering the practice of BIM application in Hong Kong, this study summarizes four strategic responses to innovative technology uptake. As demonstrated in Figure 15, they are pioneer/leading innovation strategy, follower/opportunity seeking strategy, wait-and-see strategy, and resistance/ avoidance strategy. The detailed definitions of the four strategies are described in the following section.

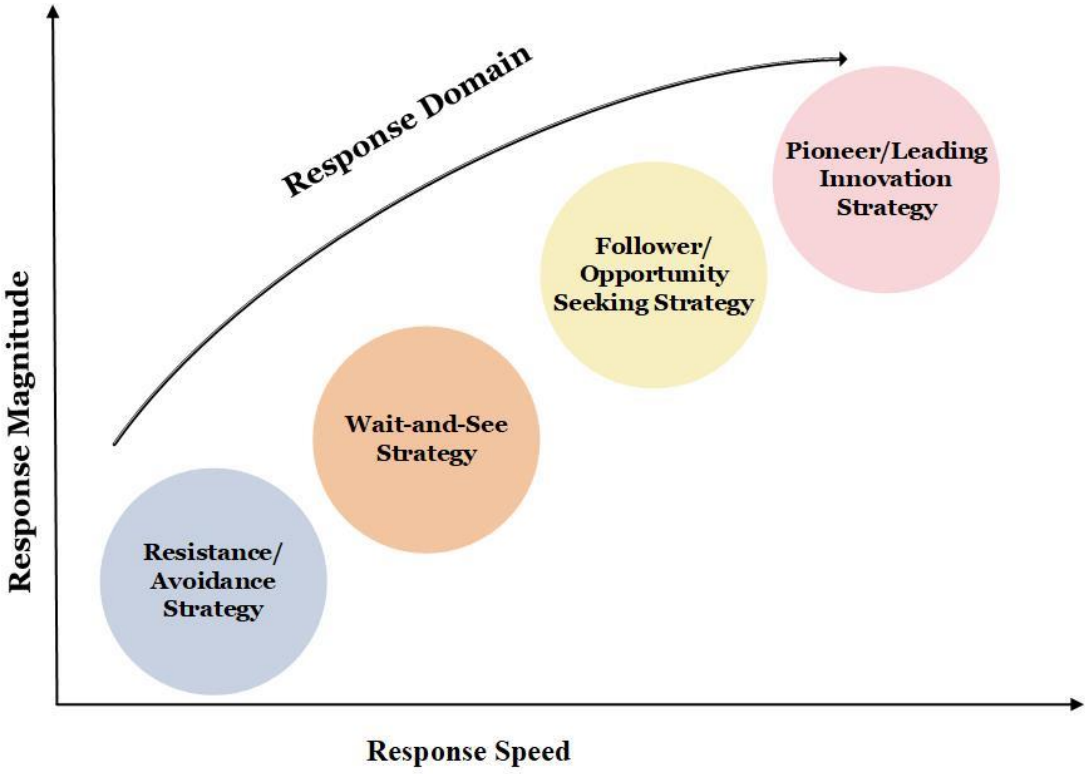


Figure 15 Framework of organizational strategic responses to innovative technology

6.2.2 Effect of Organization’S Dynamic Capability on Strategic Response

This section follows the definition of dynamic capabilities proposed by (D. J. Teece et al., 1997) presented in the literature review section. The dynamic capability was developed from the absorptive capability theory proposed by Cohen and Levinthal (1990), combinative capabilities theory proposed by Kogut and Zander (1992), and capabilities theory proposed by Amit and Schoemaker (1993) (Y. Lin & Wu, 2014). Dynamic capability theory is widely used to explore the uneven development of different organizations within the same industry and explain the competitive advantage gained by some organizations in the market (Jiang, Chai, Shao, & Feng, 2018; Ozaki, 2003; D. Teece & Pisano, 2003). Verona and Ravasi (2003) also suggested that the development of an organization’s dynamic capabilities can be an effective way to respond to the environment and competition in a highly innovative climate. Further, the study also found that organizations with superior dynamic capabilities tend to be more likely to achieve long-term performance retention (Schoemaker, Heaton, & Teece, 2018). Drawing on the characteristics of dynamic capability proposed by D. J. Teece et al. (1997) in 1997, Y. Lin and Wu (2014) further developed and summarized three components that represent the dynamic capability of organizations: integrating capability, learning capability, and reconfiguring capability.

Integration capability effectively integrates internally available resources and external technologies into the internal production process (Siagian, Jade, & Tarigan, 2020; Zahra & Nielsen, 2002). With the transformation of internal sources and the adoption of external technologies, the organization is able to develop a response strategy (Joel West & Gallagher, 2006). Recently, Wijethilake (2017) also proved that integration ability is positively associated with the strategic response to innovation initiatives. BIM is an innovative technology that has achieved a transition of design tasks from drawings to computers in the construction industry. The successful implementation usually requires effective integration of current internal sources. For example, some organizations will quickly respond by integrating relevant/previous experience or elaborating on the existing technology and related personnel to facilitate BIM application. In contrast to organizations that have the related experience, some organizations may fail to actively respond to the application of BIM due to the ineffective integration. Hence, the following set of hypotheses has been proposed to explore the impact of integration capability on an organization's response to innovation:

H1a: Organization's integration capability has a positive effect on the decision to adopt Pioneer/Leading Innovation Strategy

H1b: Organization's integration capability has a positive effect on the decision to adopt Follower/Opportunity Seeking Strategy

H1c: Organization's integration capability is negatively associated with the decision to adopt Wait-and-See Strategy

H1d: Organization's integration capability is negatively associated with the decision to adopt Resistance/ Avoidance Strategy

The learning capability corresponds to firms’ ability to acquire, store, and process knowledge (Simonin, 2004), allowing organizations to enhance existing capabilities through both cross-organizations and inter-organizations learning. Carneiro (2000) also pointed out that in the face of technological innovation in the industry, organizations often actively learn to improve their competitiveness. By learning from other organizations and within their own organization, new skills can be created, and existing skills can be developed in unique circumstances. Considering the specificity of BIM, the implementation of such technology requires active learning ability. The organizations may differ in their response strategies depending on differences in the degree of existing learning ability.

On the one hand, some organizations will participate in BIM knowledge learning/training programs organized by the government/industry and hold frequent internal cross-department BIM knowledge sharing/learning programs. On the other hand, some organizations may choose to learn from collaborators when collaborating with external organizations in conducting BIM-related projects. The following set of hypotheses is proposed to examine the organization’s learning capability:

H2a: Organization's learning capability has a positive effect on the decision to adopt Pioneer/Leading Innovation Strategy

H2b: Organization's learning capability has a positive effect on the decision to adopt Follower/Opportunity Seeking Strategy

H2c: Organization's learning capability is negatively associated with the decision to adopt Wait-and-See Strategy

H2d: Organization's learning capability is negatively associated with the decision to adopt Resistance/ Avoidance Strategy

Reconfiguring capability ability is defined as the ability of companies to redeploy existing resources and adjust existing practices in the face of changes within the industry (Michaelis, Rogbeer, Schweizer, & Özleblebici, 2021; Zahra, Sapienza, & Davidsson, 2006). As part of organizational routines, reorganization capabilities play an essential role in a company's ability to increase the organization's adoption rate of innovative technologies and radical innovation (Feldman, 2000; Mousavi, Bossink, & van Vliet, 2018). Given the fact that BIM has evolved from traditional construction technologies, organizations can leverage and reorganize existing resources to respond to the impact of innovative technologies on the industry. The response to innovative technologies also varies based on the different levels of reconfiguring capabilities. For example, while some organizations can directly respond to changing policy/standards by reorganizing their resources, others are limited to accommodating the needs of their partners based on reconfiguring ability and the existing resources available when handling BIM-related issues. These discussions lead to the following four research hypotheses:

H3a: Organization's reconfiguring capability ability has a positive effect on the decision to adopt Pioneer/Leading Innovation Strategy

H3b: Organization's reconfiguring capability has a positive effect on the decision to adopt Follower/Opportunity Seeking Strategy

H3c: Organization's reconfiguring capability is negatively associated with the decision to adopt Wait-and-See Strategy

H3d: Organization's reconfiguring capability is negatively associated with the decision to adopt Resistance/ Avoidance Strategy

As proposed by Kamara, Augenbroe, Anumba, and Carrillo (2002), the implementation of innovation in the AEC industry is a complicated process that requires several key steps, including the conceptualization of an idea, transfer of knowledge, and collaboration among different stakeholders (Xue, Zhang, Yang, & Dai, 2014). Construction-related companies need to propose different strategies according to their capabilities and resources to plan the technological innovation adoption process and effectively achieve long-term competitiveness. While most studies focus on understanding the relationship between dynamic capability and organizational performance, there is a lack of research on the impact of dynamic capability on the strategic response, making it difficult for managerial decision-making when faced with innovative technology. Therefore, the set of research hypotheses mentioned above is proposed to explore the association between dynamic capability and different strategies at the organizational level.

6.2.3 Effect of Organization’s Social Status on Strategic Response

Social status related to a field is generally defined as individual differences in occupying a core or peripheral position in a network (Anheier, Gerhards, & Romo, 1995; Zietsma, Groenewegen, Logue, & Hinings, 2017). Core actors often have significant influence and can leverage their influence to respond proactively to the innovative requirement in the industry and lead change within the industry, in other words, leading the revolution within the industry (Naumovska, Gaba, & Greve, 2021; Owen, Pansera, Macnaghten, & Randles, 2021). The definition of the social status usually consists of multiple variables, such as resources, leadership, and membership in the organization (Mayer & Roberta, 2017; Wayne, Shore, & Liden, 1997). In previous studies, scholars have explored the role of social status in achieving different levels of success for various stakeholders in the face of processes related to institutional change (Dess et al., 2003; Meijer & Bolívar, 2016). In addition, due to differences in social status, there are also distinctions in individuals' access to resources and their orientation to take risks in the adoption of innovative technologies (Hemphälä & Magnusson, 2012). Thus, the social status of organizations plays a significant role in the adoption decision and response strategy.

Due to the unique characteristics of the construction industry, the completion of a project relies on cooperation among different types of organizations, including, but not limited to, owners, architect designers, engineers, contractors, and sub-contractors. With a growing number of studies focusing on investigating the social status and its impact, the objective representation of an organization's social status in the industry has become a central issue. For example, through a questionnaire survey and interview, prior research has argued the increasingly prominent position of general contractors instead of the architect (Xie, Wu, Luo, & Hu, 2010), while Heravi, Coffey, and Trigunarsyah (2015) presents an opposing opinion that, as the link between the owner and the other stakeholders becomes more prominent in the design consultants are often considered more central to the construction project These contrasting results may be due to differences in the measurement criteria chosen and/or how data was collected. Thus, limited understanding of the organizational social status and the lack of measurable models make it difficult to explore how social status influences innovation decisions.

The specific characteristics of the BIM implementation practices in Hong Kong’s construction industry indicated a core-periphery structure in the regional collaboration network regarding the BIM-related project. In detail, some organizations have adopted BIM technology in the early period and occupied a core position in the industry, while others are still in the preliminary stage of BIM adoption due to the organization's scale or attributes. Relying on a social network analysis of longitudinal data collected from BIM-based construction projects in Hong Kong over the past decade (2008-2017), this study has successfully simulated the evolution of sub-collaboration and whole networks in the regional construction industry in Chapter 4 and Chapter 5, respectively. The centrality of organizations in the final year was calculated and represented by the degree centrality and eigenvector centrality. These indicators propose a measurable model of an organization's social status by conceptualizing and deriving specific empirical data. Since the construction industry in Hong Kong is relatively small in size, it is more feasible to explore the impact of social status on various organizations in response to the innovative technology in the regional construction industry. Thus, the following hypotheses are proposed based on the previous discussion.

Thus, the following set of hypotheses is proposed based on the previous discussion.

H4a: Organization's social status has a positive effect on the decision to adopt Pioneer/Leading Innovation Strategy

H4b: Organization's social status has a positive effect on the decision to adopt Follower/Opportunity Seeking Strategy

H4c: Organization's social status is negatively associated with the decision to adopt Wait-and-See Strategy

H4d: Organization's social status is negatively associated with the decision to adopt Resistance/ Avoidance Strategy

Drawing on the network perspective, this study converges organizational social status and dynamic capability to explore the relationship between organizational characteristics in the former inter-organization collaboration network with the latter strategic response to innovation. The measurement development and data analysis results are presented in the following sections. Based on the discussion above, the theoretical model of this research is shown in 16.

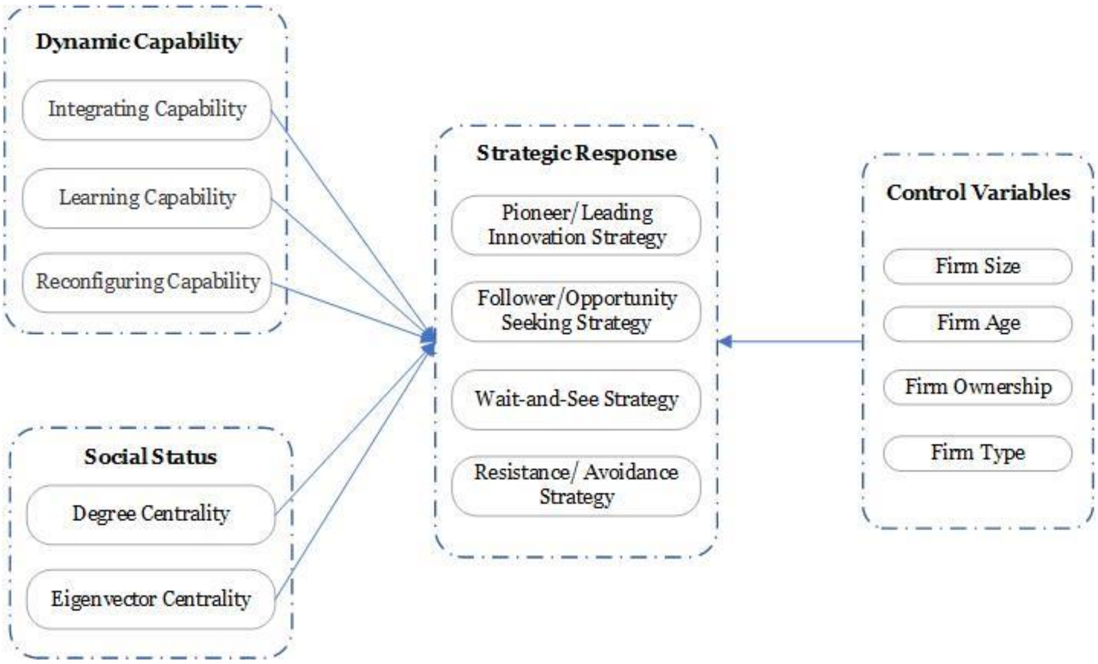


Figure 16 Theoretical model

6.3 Research Method

6.3.1 Measurements Development

In this section, a questionnaire was firstly designed to investigate the organization's strategic response to BIM and the affecting factors. As a continuation to the questionnaire designed in Chapter 5, the first section of the questionnaire explored background information of the respondents' company, including firm type, firm ownership, firm size, and firm age. The second section presented the measurement scales for dynamic capability. In the third section, a set of questions invite the respondents to provide their possible/recent decision in adopting BIM technology at the firm level. A seven-point Likert scale was used, ranging from “1” (strongly disagree) to “7” (strongly agree).

Independent Variables

The independent variables in the construct consisted of two parts, namely, the dynamic capabilities and ego network indicator. The measurement of dynamic capabilities was following the scale defined by (D. J. Teece et al., 1997) with the underlying dimensions of (1) Integrating Capability, (2) Learning Capability, (3) Reconfiguring Capability, and were further developed according to the characteristics of the regional construction industry. Concerning the measurement of social status, the scale was specified and classified from the analysis results of ego network indicator (i.e., degree centrality, eigenvector centrality), which objectively reflects organizations' social status.

Degree centrality in a social network is defined as the number of links directly attached to a node (i.e., the number of ties that a node has) (Freeman, 1978). This indicator is regarded as a primary measure of the node in the ego network, with a high degree of centrality reflecting a more prominent position in the whole network. Different from the degree centrality, which counts the number of ties connected to the node, the eigenvector centrality defines a node's degree with an eigenvector coefficient. To be specific, eigenvector centrality measures the influence of a node in the ego network. When a node is connected to a high-scoring node, the node itself is also regarded as influential and attractive in the whole network (Bonacich, 2007). As a result, these two indicators provide a quantitative way to measure the social status of an organization.

The degree centrality and eigenvector centrality are calculated from a numerical data range of 0.005-0.33. In order to conduct the subsequent correlation and regression analysis, this study classifies the two centralities into four types to represent the social status (1= below 0.015, 2=0.015-0.04, 3=0.04-0.1,4=above 0.1), the higher number reflecting a more central position. Similarly, the eigenvector centrality is also divided into three groups: (1= below 0.1, 2= 0.1-0.2, 3=over 0.2), the higher value representing a broader influence on other nodes.

Control Variables

Four control variables were adopted to analyze the impact of the organization's dynamic capabilities and social status on strategic response to BIM. The firm size was divided into four categories according to the total full-time employees in the organization (1=0-50, 2=50-100, 3=1000-10000, 4= above 10000). The firm ownership type was measured as a dummy variable which reflects whether the surveyed organization was a local or overseas company (0=local company, 1=oversea company). Third, the firm age was divided into four categories according to the organization's established year (1=under 10, 2=10-50,3=50-100,4=above 100). And firm type follows the same classification in Chapter 4 (1=owner, 2=design consultant,3=main contractor). The detailed definition and code of each construct are listed in Table 18.

Table 18 Measurement items and definition of constructs

Construct	Code	Definition
Dynamic Capabilities		
Integrating Capability (IC)	IC1	Our firm is able to integrate and draw on relevant/previous experience in the application of innovative technologies when handling BIM-related issue
	IC2	Our firm is able to integrate and

		elaborate the existing technology and related personnel when handling BIM-related issue
	Organizational Support	
Learning Capability (LC)	LC1	Our firm participates in frequent external BIM knowledge learning/training programs organized by the government /industry
	LC2	Our firm holds frequent internal cross-department BIM knowledge sharing/learning program
	Inter-organizational Support	
	LC3	When collaborating with external organizations in conducting BIM-related projects, our firm is able to proactively uses BIM
	LC4	When collaborating with external organizations in conducting BIM-related projects, our firm is able to cooperate based on existing experience and is willing to learn from collaborators
Reconfiguring Capability (RC)	RC1	Our firm is able to reconfigure and respond to meet changing government policy and industry-standard rapidly
	RC2	Our firm is able to reconfigure and respond to changing market needs and trends rapidly
	RC3	Our firm is able to reconfigure and respond to the competitors' actions rapidly
	RC4	Our firm is able to conduct effective communication and cooperation with

		other cooperators when facing the reconfigure of BIM-related resources
Social Status		
Degree Centrality	DEC	The number of direct connections between each node and the rest nodes in the network
Eigenvector Centrality	EIC	The extended connections of a node and its influence on the whole network

This study has proposed a new scale of strategic responses to innovative technology, drawing on the different combinations of response domain, speed, and magnitude. Detailed definitions are provided as follows:

(1) Pioneer/Leading Innovation Strategy (PLIS): the organization actively responds to BIM development requirements to strive for or maintain a leading position in the industry or meet anticipated BIM development requirements in advance to cater to the needs of clients or collaborators.

(2) Follower/Opportunity Seeking Strategy (FOSS): the organization closely follows the leading organizations in the industry and seeks partnership opportunities to advance the use of BIM technology in the process of working with leading organizations

(3) Wait-and-See Strategy (WSS): Organizations choose to wait and see the development of BIM in the industry and decide whether to adopt BIM based on their resources and management capabilities

(4) Resistance/ Avoidance Strategy (RAS): Organizations choose to avoid conforming with BIM adoption, e.g., avoid participating in projects requiring the use of BIM or collaborating with organizations requiring the use of BIM

Combined with the BIM adoption practices in the regional construction industry, the detailed measurement items and definition of the four organizational strategic responses mentioned above are presented in Table 19.

Table 19 Measurement items and definition of strategic response

Strategic Response	Code	Definition
Pioneer/Leading Innovation Strategy	PLIS1	Our firm is willing to set up/upgrade the BIM department to maintain a good level of application of innovative technologies
	PLIS2	Our firm is willing to draw up a firm-level strategic plan (e.g., three or five years formal plans) for BIM implementation to maintain a good level of application of innovative technologies
	PLIS3	Our company is willing to actively respond to policy requirements or standard changes related to BIM implementation in the regional industry
Follower/Opportunity Seeking Strategy	FOSS1	Our firm is willing to train staff/purchase hardware to meet the requirement of the government or other project partner
	FOSS2	Our firm is willing to develop a standard/guide for BIM implementation to meet the requirement of the government or other project partner
	FOSS3	Our firm is willing to work closely with partners to maintain and advance the level of BIM adoption (e.g., rate of BIM-involved projects, rate of BIM-capable staff)
Wait-and-See Strategy	WSS1	Our firm prefers to follow guidelines or partners' requirements to adopt BIM in current projects
	WSS2	Our firm prefers to consider developing BIM-related goals in future projects
Resistance/ Avoidance Strategy	RAS1	Our firm faced some resistance in adopting/promoting the application of BIM
	RAS2	Our firm will not actively seek BIM cooperation projects

6.3.2 Sampling and Data Collection

Following the questionnaire results, follow-up semi-structured interviews were conducted with 33 organizations, including eight owners, fifteen design consultants, and ten main contractors. The face-to-face interviews range from half an hour to an hour, and interviews were transcribed verbatim (a total of 49,352 words). The transcripts provide an industry practice reference for subsequent measurement criteria and regression results analysis. The demographic information of the 204 surveyed organizations is presented in 20.

Table 20 Demographic information of surveyed organizations

Items	Categories	N	Percent (%)	Cumulative Percent (%)
Firm Size	under 50	19	9.31	9.31
	50-1000	114	55.88	65.20
	1000-10000	51	25.00	90.20
	above 10000	20	9.80	100.00
Firm Age	under 10	10	4.90	4.90
	10-50	138	67.65	72.55
	50-100	42	20.59	93.14
	above 100	14	6.86	100.00
Firm Ownership	local company	147	72.06	72.06
	oversea company	57	27.94	100.00
Firm Type	owner	64	31.37	31.37
	designer	80	39.22	70.59
	contractor	60	29.41	100.00
Total		204	100.0	100.0

6.4 Data Analyses Results

Using the collected data from the questionnaires and semi-structured interviews, together with the ego characteristics calculated from social network analysis, the data analysis presented in this section follows the following three steps to test the theoretical model and the proposed research hypotheses. Firstly, the validation and assessment of the measurement, and secondly, the descriptive analysis and correlation analysis on the strategic response to BIM. Finally, a hierarchical regression analysis of the organization’s dynamic capabilities, ego characteristics in the social network, and the strategic response to BIM is performed.

6.4.1 Measurement Validation

This section validates the measurement proposed in section 6.3.1 using SPSS version 21.0 and Amos version 21.0. Firstly, Cronbach's alpha test was used to test the reliability of the questionnaires. Developed by Cronbach (1951), Cronbach's alpha test provides a reasonable index measure of internal consistency, which is widely used in empirical data analysis (McNeish, 2018). Generally, the higher the Cronbach's alpha value represents better internal consistency of the questionnaire. In detail, when the Cronbach's alpha value of the scale designed in the questionnaire is lower than 0.7, it indicates that the scale's internal consistency is poor, while a Cronbach's alpha value greater than 0.9 represents an excellent internal consistency, and the measurement is high-reliability. As demonstrated in Table 21, the result of Cronbach's alpha test of the seven variables ranges from 0.751 to 0.888, which is higher than the recommended criterion of 0.7. Thus, the reliability analysis indicates that the proposed measures are considered to have an adequate level of inter consistency.

Table 21 Analysis result of Cronbach's alpha test

Construct	N of Items	N	Cronbach α
IC	2	204	0.751
LC	4	204	0.834
RC	4	204	0.870
PLIS	3	204	0.819
FOSS	3	204	0.888
WSS	2	204	0.879
RAS	2	204	0.869

Before further factor analysis, the KMO (Kaiser-Meyer-Olkin) test and Bartlett spherical test have been conducted in SPSS to determine whether the collected data is suitable for index concentration and reconstruction. According to the analysis results, the KMO value of this study is 0. 852, which is greater than the recommended criterion of 0.8 (Cronbach, 1951). As for Bartley's test, the approximate chi-square value is 4274.940, and the significance probability is 0.000, which is less than 0.01. Therefore, the null hypothesis of the Bartlett test is rejected, in line with the conditions of further factor analysis. Considering that some measurements of dynamic capabilities are newly proposed to match the strategic response to BIM, both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) are required to examine the reliability and validity of the measurement (Fullerton, Kennedy, & Widener, 2014).

Table 22 Result of exploratory factors analysis

Measurement Items	Factor loading (Rotated)							
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Communalities
IC1	0.02	-0.037	0.165	0.134	0.023	**0.883**	-0.111	0.84
IC2	0.094	-0.053	0.171	0.106	-0.012	**0.864**	0.167	0.827
LC1	-0.009	**0.902**	0.152	0.034	0.093	-0.051	0.071	0.854
LC2	-0.045	**0.756**	0.141	0.093	-0.118	-0.072	0.075	0.626
LC3	-0.09	**0.783**	0.069	-0.038	0.148	0.002	0.042	0.652
LC4	0.047	**0.763**	0.049	0.14	0.17	0.033	0.063	0.641
RC1	**0.84**	-0.01	0.102	0.113	0.144	0.076	0.172	0.785
RC2	**0.798**	-0.061	0.098	0.061	0.194	-0.003	0.146	0.713
RC3	**0.751**	-0.033	0.078	0.228	0.07	0.13	0.239	0.701
RC4	**0.823**	-0.024	0.234	0.183	0.07	-0.023	0.008	0.772
PLIS1	0.185	0.088	0.149	**0.842**	0.207	0.108	0.15	0.849
PLIS2	0.258	0.105	0.13	**0.747**	0.155	0.149	0.085	0.706
PLIS3	0.105	0.045	0.245	**0.777**	0.085	0.057	0.148	0.709
FOSS1	0.19	0.105	**0.855**	0.193	0.135	0.123	0.171	0.878
FOSS2	0.217	0.168	**0.809**	0.203	0.126	0.206	0.068	0.833
FOSS3	0.128	0.26	**0.742**	0.198	0.173	0.16	0.211	0.774
WSS1	0.21	0.163	0.193	0.243	**0.829**	0.015	0.146	0.877
WSS2	0.28	0.159	0.201	0.219	**0.812**	-0.002	0.181	0.884
RAS1	0.269	0.147	0.262	0.201	0.143	0.01	**0.81**	0.879
RAS2	0.306	0.149	0.156	0.206	0.194	0.049	**0.812**	0.883
Variance Explained (%)	15.52	14.07	11.97	11.69	8.43	8.41	8.32	N/A
Cumulative Variance Explained (%)	15.52	29.59	41.56	53.25	61.68	70.09	**78.41**	N/A

Note: The values shown in bold font represent the factor loading of each measurement item on their intended constructs

EFA was first conducted in SPSS to test whether the 20 measurement items listed in Table 22 captured the latent constructs well. As shown in Table 22, the rotated factor loading of the measurement items on their intended constructs is all higher than the recommended criterion of 0.8 (Williams, Onsman, & Brown, 2010) and larger than the loadings of other constructs. At the same time, the cumulative interpretation rate of variance reached 78.407%, which indicated that the designed scale had a reasonable degree of interpretation. As a result, no observed variable needs to be deleted from the proposed model.

CFA was then conducted in Amos to further verify the reliability and validity of the measurement items proposed in the model. Considering that the model in this section has a multivariate estimation program of 20 latent variables, and the sample data conforms to normal distribution, the maximum likelihood (ML) method was selected for model estimation.The goodness of fit of the model is shown in Table 23. The results show that the indices of all the multi-items (i.e., IC, RC, LC, DEC, and EIC) in the measurement model satisfy their corresponding acceptable requirements, indicating that the estimated measurement model provides a good fit for the data. Similar to Cronbach's α, construct reliability (CR) and the average of variance extracted (AVE) are reliability indexes for testing latent variables. The higher the value of the CR represents the better consistency of the internal consistency, and the 0.7 is an acceptable threshold (Fornell & Larcker, 1981). AVE calculates the explanatory power of variation of latent variables. Similarly, the higher AVE reflects the greater the percentage of variation of indicator variables explained by latent variables. Fornell and Larcker (1981) suggested that the ideal value should be greater than 0.5.

Table 23 Goodness-of-fit of the model

Goodness-of-fit measure		Level of acceptance fit	Fit statistics	Judgment
Absolute fit	χ^2/df	<5 acceptable; <3 good	1.088	√
	GFI	>0.8 acceptable; >0.9 good	0.930	√
	RMSEA	<0.1 acceptable; <0.08 good	0.021	√
Incremental fit	NFI	>0.9	0.934	√
	IFI	>0.9	0.994	√
	TLI	>0.9	0.993	√
	CFI	>0.9	0.994	√

Table 24 Result of measurement validity and construct correlations

			Correlation Matrix						
Factor	AVE	CR	IC	LC	RC	PLIS	FOSS	WSS	IC
IC	0.618	0.762	**0.786**						
LC	0.65	0.87	-0.042	**0.806**					
RC	0.643	0.876	0.161	-0.006	**0.802**				
PLIS	0.709	0.869	0.283	0.196	0.439	**0.842**			
FOSS	0.754	0.9	0.361	0.33	0.41	0.507	**0.868**		
WSS	0.787	0.88	0.1	0.296	0.461	0.508	0.479	**0.887**	
RAS	0.78	0.876	0.122	0.27	0.518	0.481	0.508	0.502	**0.883**

Notes: [a] AVE= average of variance extracted CR= construct reliability
[b] The values shown in bold font represent the square root of AVE

The CR and AVE of the examined multi-item constructs are shown in Table 24. The analysis result reports that the values of these indices (AVE>0.5, CR>0.7, factor loading>0.7) all satisfy the acceptable requirements. Furthermore, as shown in Table 24, the square root of AVE (values on the diagonal of the correlation matrix) are greater than the absolute value of the inter-structural correlation (non-diagonal value), indicating reasonable reliability and validity of the constructs in the proposed model. Table 25 presents the result of the confirmatory factor analysis. The standardized estimate of the 20 lanterns in the model ranged from 0.644 to 0.972, all above the threshold of 0.5. Also, the corresponding p-values were all less than 0.05, indicating statistical significance between each potential variable and the observed variable. As a result, the proposed measurement model has adequate reliability and convergent validity.

Table 25 Results of confirmatory factor analysis

Factor	Observation Variable	Coef.	Std. Error	C.R.	p	Std. Estimate
Factor1	IC1	1.000	-	-	-	0.757
Factor1	IC2	0.788	0.121	6.512	0.000	0.841
Factor2	LC1	1.000	-	-	-	0.972
Factor2	LC2	0.469	0.045	10.430	0.000	0.644
Factor2	LC3	0.527	0.045	11.629	0.000	0.698
Factor2	LC4	0.544	0.046	11.755	0.000	0.703
Factor3	RC1	1.000	-	-	-	0.856
Factor3	RC2	0.687	0.056	12.223	0.000	0.760
Factor3	RC3	0.798	0.063	12.624	0.000	0.778
Factor3	RC4	0.788	0.062	12.729	0.000	0.783
Factor4	PLIS1	1.000	-	-	-	0.929
Factor4	PLIS2	0.577	0.047	12.277	0.000	0.757
Factor4	PLIS3	0.504	0.044	11.370	0.000	0.712
Factor5	FOSS1	1.000	-	-	-	0.907
Factor5	FOSS2	0.779	0.047	16.497	0.000	0.862
Factor5	FOSS3	0.705	0.047	14.887	0.000	0.810
Factor6	WSS1	1.000	-	-	-	0.862
Factor6	WSS2	0.922	0.068	13.550	0.000	0.919
Factor7	RAS1	1.000	-	-	-	0.883
Factor7	RAS2	0.843	0.063	13.469	0.000	0.884

Note: [a] Coef.=coefficient S [b] td. Error= standardized Error [c] Std. Estimate= standardized estimate

6.4.2 Descriptive Analysis and Correlation Analysis

The results of the descriptive analysis shown in Table 26 indicate that the dynamic ability is in an average range, with learning ability having the highest value, indicating that the learning capability of the organization is the most substantial consideration when proposing a strategy to adopt innovative technology. Specifically, the highest mean value of LC1 shows that frequent participation in external BIM training organized by the government or affiliated institutions is the most important component for reflecting and enhancing organizational learning ability. Regarding the strategic response, further descriptive results found that the organization's decision on strategy is heterogeneous. In detail, the highest mean value of FOSS (as shown in Table 26) reflects a large number of organizations in the regional construction industry choose to follow the pioneering organizations and seek potential collaboration opportunities in the adoption of BIM.

Table 26 Descriptive statistics of measurement items

Variable	Items	N of samples	Mean	Std. Deviation
IC	IC1	204	3.745	1.954
	IC2	204	3.593	1.385
LC	LC1	204	4.127	1.801
	LC2	204	3.77	1.275
	LC3	204	3.868	1.323
	LC4	204	3.779	1.356
RC	RC1	204	3.824	1.843
	RC2	204	3.775	1.424
	RC3	204	3.77	1.616
	RC4	204	3.701	1.586
PLIS	PLIS1	204	4.039	1.995
	PLIS2	204	3.794	1.413
	PLIS3	204	3.858	1.311
FOSS	FOSS1	204	4.211	2.044
	FOSS2	204	4.093	1.675
	FOSS3	204	4.201	1.614
WSS	WSS1	204	4.02	2.27
	WSS2	204	3.971	1.965
RAS	RAS1	204	3.814	2.071
	RAS2	204	3.833	1.742

To further investigate the correlation between PLIS, FOSS, WSS, RAS, and the nine items of Firm Size, Firm Age, Firm Ownership, Firm Type, IC, LC, RC, DEC, EIC, respectively, the Pearson Correlation analysis was conducted in this section. The correlation analysis results presented in Table 27 indicate a noticeable difference in relation to the strength of the correlation among the dynamic capability and social status with the innovation strategy.

As can be seen from the table, the correlation coefficient among PLIS and Firm Type, IC, LC, RC, DEC, EIC are 0.095, 0.355, 0.283, 0.196, 0.439, 0.574, 0.679, respectively, which indicates a significant positive correlation between PLIS and the six independent variables. Meanwhile, the p-value of the correlation coefficient between PLIS with Firm Ownership, Firm Size and Firm Age indicates no correlation between PLIS and the three control variables. Further, a positive correlation exists between FOSS and Firm Ownership, Firm Ownership, Firm Type, IC, LC, RC, DEC, and EIC, respectively. At the same time, the remaining two independent variables were proved to not correlate with the FOSS. With respect to WSS and RAS, the correlation analysis shows that both strategies negatively correlate with LC, DEC, and EIC. In contrast, the correlation with Firm Type and RC are proved to be positive. Meanwhile, the result also reveals no correlation between WSS and RAS with Firm Size, Firm Age, Firm Ownership, and IC, respectively.

Hence, the Pearson Correlation analysis has provided clear evidence that the strategic response is highly correlated with the Firm Type, Learning Capability, Reconfiguring Capability, and Social Status ($p<0.001$). Meanwhile, the firm size and firm age have been proved irrelevant to the organization's choice of strategic response. Another intriguing finding is that firm ownership is only relevant to the Follower and Opportunity Seeking Strategy, while integration capability is not relevant to either WSS or RAS.

Table 27 Result of Pearson correlation analysis

Variable	PLIS	FOSS	WSS	RAS
Firm Size	-0.049	-0.076	-0.019	-0.057
Firm Age	-0.096	-0.055	-0.117	-0.11
Firm Ownership	0.095	0.019**	0.026	0.025
Firm Type	0.355***	0.423***	0.451***	0.490***
IC	0.283***	0.361***	0.1	0.122
LC	0.196**	0.330***	-0.296***	-0.270***
RC	0.439***	0.410***	0.461***	0.518***
DEC	0.574***	0.489***	-0.701***	-0.605***
EIC	0.679***	0.520***	-0.587***	-0.558***

Note: * p<0.05 ** p<0.01 *** p<0.001

An independent sample T-test presented in Table 28 has shown that the local company generally has a higher dynamic capability than the overseas company. In relation to the four kinds of strategic response, the overseas company has a more obvious intention to implement the Pioneer/Leading Innovation Strategy, Wait-and-See Strategy, and Resistance/ Avoidance Strategy, but an apparent weak intention in the implementation of Follower/Opportunity Seeking Strategy. However, the p-value of the dynamic capability and strategic response with both kinds of organizations are not statistically significant at the 5% level(p-value>0,01), indicating no significant differences among them. The result also suggests that the non-significant difference in the strategic responses to innovation between local and overseas organizations may not be attributable to the different dynamic capabilities of the surveyed organizations. Regarding the social status, the mean value is slightly different between the local organizations and overseas organizations. However, the t-test of eigenvector centrality is statistically significant at the 5% level, while the t-test of degree centrality is not. In conclusion, the independent t-test reveals that the firm ownership type may affect the eigenvector centrality, where the local organization may significantly influence the collaboration network.

Table 28 Result of descriptive and comparative analysis by organizations'ownership

	Local Company		Oversea Company		Independent sample T-test		
Item	Mean	SD	Mean	SD	T-value	p-value	Difference
IC	3.664	1.558	3.693	1.410	-0.140	0.174	0.236
LC	3.903	1.197	3.842	1.175	0.364	0.869	0.670
RC	3.612	1.380	4.183	1.292	-2.818	0.473	-0.579
PLIS	3.816	1.363	4.105	1.386	-1.342	0.994	-0.289
FOSS	4.150	1.645	1.216	1.551	-0.264	0.223	0.253
WSS	3.963	2.010	4.079	2.006	-0.371	0.678	-0.166
RAS	3.796	1.798	3.895	1.819	0.914	0.363	-0.988
DEC	4.198	2.036	4.091	1.961	0.343	0.227	0.1078
EIC	4.121	1.983	4.106	1.765	-0.048	**0.044**	-0.145

Concerning the relationship between different firm types and strategic responses, the One-way ANOVA analysis (presented in Table 29) reveals that the strategic organizational responses of the surveyed owner, designers, and main contractors are significantly different (all p-value are below 0.001).). In particular, the Resistance/ Avoidance Strategy shows the most significant variability. The ANOVA analysis also indicates apparent differences among the three types of organizations in learning capabilities. In contrast, the integrating and reconfiguring capabilities of the three types of organizations are not significantly different. As shown in Table 29, the owner is generally more proactive in BIM implementation compared with designers and main contractors. A high mean value supports that the owners tend to be proactive in their choice of innovation strategy, gain an advantageous position in potential collaborations regarding innovative technologies and promote the adoption of the technology in the regional industry. In contrast to the relatively average low mean value of designers in their strategy choices, contractors possess the highest mean values in all three strategy choices except PLIS, exposing the diversity of contractors in the regional construction industry and the flexibility of their strategic options. Another interesting finding is that the contractors have the most prominent social position in the project cooperation network, with a mean value of both degree centrality and eigenvector centrality over 5.

Together with the correlation analysis presented in Table 27 and comparative analysis in Table 29, the result reveals the difference and complexity in the dynamic capabilities and social status by organizations' types and ownership in the local construction industry. The results also reveal the diversity of organizational strategies to respond to the application of innovative technologies, which are significantly affected by multiple components (especially learning capability, reconfiguring capability, and social status).

Table 29 Result of descriptive and comparative analysis by organizations’ type

	Owner		Designers		Main Contractor		ANOVA T-test
Item	Mean	Variance	Mean	Variance	Mean	Variance	F
IC	3.422	0.036	3.856	0.029	3.683	0.038	1.472
LC	3.336	0.019	3.891	0.016	4.467	0.021	16.107 ***
RC	2.664	0.016	3.650	0.013	5.100	0.017	93.419
PLIS	4.431	0.026	4.017	0.021	3.219	0.028	15.007***
FOSS	3.271	0.034	4.250	0.027	5.017	0.036	22.029***
WSS	3.930	0.051	3.906	0.041	5.250	0.052	26.010***
RAS	2.766	0.039	3.769	0.031	5.025	0.042	31.907***
DEC	3.410	0.2946	3.981	0.045	5.228	0.060	15.042***
EIC	3.321	0.051	4.032	0.041	5.057	0.055	14.445***

Note: *** p<0.001

6.4.3 Hierarchical Regression Analysis and Hypotheses Testing

To systemically investigate the driving factors on organizations’ relative strategic emphases, the ordinary least square (OLS) regression was conducted using the software SPSS 20. In detail, four hierarchical regression models were designed in this section to test the research hypotheses on the relationship between the organization’s dynamic capabilities, organizational social status, and strategic response to BIM, respectively. A block of the control variables (firm type, firm size, firm age, firm ownership) was firstly run in the model. Then, the dynamic capabilities and social status indicators were added to the model in the following two separate steps. As a development from linear regression analysis, hierarchical linear regression focuses on analyzing the data from multiple levels (Singer 1998). The hierarchical regression analysis presented in this section provides the incremental impact of strategic responses with improved explanation by controlling the effects of dynamic capability and social status. The variance inflation factors (VIFs) for the variables range from 1.072-1.875, which are all under the recommended VIF threshold of 10. Therefore, multicollinearity will not affect the regression results (Dormann et al., 2013).

The analysis result (presented in Table 30) shows that dynamic capability and social status are excluded from the regression model in Model 1, Model 4, Model 7, and Model 10. The four control variables only explain 0.13, 0.186, 0.219, 0.252 in PLIS, FOSS, WSS, RAS, respectively. Regarding the separate effect of the control variables on the strategic responses, organization ownership is found to have a significant positive relationship with PLIS ($\beta = 0.045, p < 0.01$, and a significant negative association with FOSS ($\beta = 0.045, p < 0.05$), while the relationship between WSS and RAS is not significant (p>0.05). There is a significant positive relationship between organization type and all four dependent variables, suggesting that strategic responses are affected by the diverse types of organizations.

When the dynamic capability variable is included in the model, the variance in the four strategic responses increases. The increment ranges from 0.1-0.27, and all the F-values are significant at a 5% level. Hence, the regression model provides reasonable evidence that the strategic responses could be affected by the dynamic capability of the organization. With regards to the separate effect of dynamic capability on the dependent variable, Table 30 demonstrates that the integration capability has a significant positive impact on the PLIS ($\beta = 0.201, p < 0.001$) and FOSS $\beta = 0.340, p < 0.001$). In contrast, Model 8 and Model 11 suggest that the integration capability is not associated with WSS or RAS (p>0.5). Thus, H1a and H1b were accepted, while H1c and H1d were rejected. The regression results in Model 2 and

Model 5 indicate that learning capability positively affects the PLIS $(\beta = 0.265, p < 0.001)$ and FOSS $(\beta = 0.428, p < 0.001)$, and have a negative effect on WSS $(\beta = -0.462, p < 0.001)$ and RAS $(\beta = -0.360, p < 0.001)$, respectively. Therefore, H2a, H2b, H2c, and H2d, are accepted. As demonstrated in Model 2 and Model 8, the reconfiguring capability is positively correlated with PLIS $(\beta = 0.432, p < 0.001)$, and WSS $(\beta = 0.605, p < 0.001)$, respectively. In contrast, the reconfiguring capability is found to have a negative association with FOSS $(\beta = -0.372, p < 0.001)$ and RAS $(\beta = -0.594, p < 0.001)$. Hence, the H3a and H3d were all accepted, while the H3b and H3c were rejected.

When the degree centrality and eigenvector centrality are added into the regression model, the variance in all the dependent variables significantly increases. The increment is 0.269 in PLIS $(F = 26.822, p < 0.001)$, 0.099 in FOSS $(F = 19.899, p < 0.001)$ 0.272 in WSS $(F = 30.560, p < 0.001)$ and 0.161 in RAS $(\beta = 23.265, p < 0.001)$. This result suggests the significantly important role an organization's social status plays in formulating a strategic response to the implementation of BIM. As also shown in Table 30, the associations of DEC with PLIS $(\beta = 0.136, p < 0.01)$ and FOSS $(\beta = 0.147, p < 0.05)$ are statistically significant and positive, while a significant negative association has been revealed with WSS $(\beta = -0.481\ , p < 0.001)$ and RAS $(\beta = -0.292\ , p < 0.001)$. As further demonstrated in Table 30, a similar result can be drawn in the association between EIC and the four dependent variables, where the EIC are revealed to be a positive associated with PLIS and FOSS at a significant level. At the same time, the WSS and FOSS are negatively associated with EIC. Based on the results from the regression model, the H4a, H4b, H4c, and H4d were all supported by the empirical data.

Table 30 Hierarchical regression results

	PLIS			FOSS			WSS			RAS		
Variables	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10	Model11	Model12
Size	0.001	0	0.002	-0.041	-0.043	-0.052	0.154	0.149	0.086	0.051	0.048	0.015
Age	-0.131	-0.081	-0.09	-0.029	0.035	0.025	-0.272	-0.267	-0.297*	-0.193	-0.176	-0.195
Ownership	0.045	0.084	0.243	-0.282	-0.183	-0.059	-0.397	-0.32	-0.043	-0.377	-0.329	-0.141
Type	0.607***	-0.095	-0.138	0.904***	0.157	0.123	1.204***	0.191	0.116	1.167***	0.23	0.179
IC	-	0.201***	0.147**	-	0.340***	0.305***	-	0.043	-0.007	-	0.055	0.015
LC	-	0.265**	0.129	--	0.428***	0.326***	-	-0.462***	0.250**	-	-0.360***	0.212*
RC	-	0.432***	0.188*	-	-0.372***	0.196*	-	0.605***	0.261*	-	-0.594***	0.348***
DC	-	-	0.136**	-		0.147*	-	-	-0.481***	-	-	-0.292***
EC	-	--	0.322***	-	-	0.183**	-	-	-0.161*	-	-	-0.167**
R^2	0.13	0.285	0.554	0.186	0.381	0.48	0.219	0.317	0.586	0.252	0.358	0.519
Adj R^2	0.113	0.26	0.534	0.169	0.359	0.456	0.203	0.293	0.567	0.237	0.335	0.497
F value	F=7.444***	F=11.169***	F=26.822***	F=11.340***	F=17.214***	F=19.899***	F=13.926***	F=13.001***	F=30.560***	F=16.794***	F=15.623***	F=23.265***
△R^2	0.13	0.155	0.269	0.186	0.195	0.099	0.219	0.098	0.269	0.252	0.106	0.161
△F Value	F=7.444***	F=14.166***	F=58.620***	F=11.340***	F=20.582***	F=18.526***	F=13.926***	F=9.412***	F=63.158***	F=16.794***	F=10.764***	F=32.460***

6.5 Discussions and Implications

6.5.1 Categorizing the Strategic Response to BIM Implementation

Although some scholars have emphasized the impact of an organization's strategic response to the external environment in the adoption of innovative technologies (Damanpour et al., 2009; Jay, 2013), there is still remarkably scant research available on how to granularize and quantify strategic responses to innovation from the organizational level. While previous studies have summarized a few key components of a strategic response to innovative technology adoption, this chapter further develops the conceptual model proposed by R. P. Lee and Grewal (2004), and theorizes four specific strategic responses based on BIM implementation practices in the Hong Kong construction industry. In detail, by conceptualizing the overlapping aspects of the three response indicators, while invoking a timing strategy (Klingebiel & Joseph, 2016), a formal strategic planning process with planning flexibility (Dibrell, Craig, & Neubaum, 2014), and a resource/routines based view (Bakar & Ahmad, 2010; Terziovski, 2010), this chapter puts forward four strategic responses to BIM adoption at the organizational level. The descriptive results demonstrate the diversity of regional organizations in terms of their strategic response. In particular, when confronted with the decision to adopt BIM, the majority of organizations choose to follow pioneering organizations and seek out potential collaboration opportunities to facilitate the implementation of innovative technology.

This result has further supported previous research findings that BIM adoption in Hong Kong is still at a primitive stage (D. W. Chan, T. O. Olawumi, & A. M. Ho, 2019), where there remains no industry-wide mandate for BIM use by clients and other collaborating members (A. K. Wong et al., 2011). The result also suggested that for such a complex and innovative technology as BIM, the response strategy at an organizational level is not driven by a single factor but is formed from multiple overlapping factors, including the timing strategy and corporate resources and routines.

Together with the research findings of Strandholm, Kumar, and Subramanian (2004), strategic responses may differ between organizations within the same industry after large-scale, industry-wide environmental changes. This study helps expand the research on the strategic response at the organizational level by categorizing the strategic response to BIM implementation.

6.5.2 Impact of Dynamic Capability and Social Status on Strategic Response

Based on the categorization of the strategic response to BIM, this study further explores the underlying factors influencing the different choices of the innovation strategic response within the construction industry at the organizational level. Specifically, this study examines the impact of the organization’s dynamic capabilities as well as the social status in the early inter-organizational collaboration networks on the strategic responses to BIM adoption. The results from the correlation analysis first provide evidence that there is a noticeable difference in the relationship between dynamic capability and the social status of organizations.

In detail, results show no correlation between the organization age or size and the independent variables, while the organization type and ownership type are statistically correlated with dynamic capability and social status. Especially compared with overseas organizations, the local organizations, including the owner, design consultants, and the main contractor, show higher dynamic capabilities. This could be explained by the fact that local organizations tend to have better adaptability and a clearer understanding of how BIM technology can be readily adopted in the local construction industry, allowing them to respond to the innovative technology actively. The independent t-test results presented in Table 28 further verify this phenomenon, revealing that the eigenvector centrality of organizations is affected by the firm ownership type, where the local organization occupies an influential position and high social status in the collaboration network.

With respect to the strategic response, an interesting finding is that the firm ownership is only related to the FOSS, where the overseas company prefers to follow the leading organizations in the collaboration network when adopting BIM. To promote the adoption of BIM, the overseas organization may seek partnerships with companies that already have mature BIM practices in the regional industry. Further, the main contractors are found to have the most prominent social status relating to the application of BIM. This intriguing finding differs from previous research emphasizing that public owners, especially the government and its affiliated organizations, are in the primary leadership position for BIM development (A. K. Wong et al., 2011). Furthermore, as demonstrated in Table 29, the owners have the highest probability of choosing a pioneer/leading innovation strategy. This finding reveals that, compared with overseas organizations, the local organizations are more inclined to implement BIM technology proactively. In contrast, overseas organizations commonly choose to wait and see the local adoption status of BIM and also seek out potential collaborators to help facilitate BIM adoption.

The results from hierarchical regression also examined the research hypotheses on the impact of dynamic capability and social status on the strategic response. Firstly, the strategic responses to BIM adoption in the regional construction industry are significantly affected by the diverse types of organizations (i.e., owners, designers, and main contractors). Secondly, the regression result supports the hypotheses on the positive association between PLIS and the organization's dynamic capability (i.e., H1a, H2a, H3a, and H4a are all accepted). Therefore, with a higher level of dynamic capability, the organization is more willing to lead the development of BIM voluntarily or actively respond to the BIM adoption requirements. This research finding is also consistent with previous studies that argue dynamic capabilities can help companies anticipate the potential advantages and disadvantages of adopting innovative technologies and reconfigure existing organizational resources and processes promptly to reduce barriers in adopting innovative technologies (Piening & Salge, 2015).

Secondly, regarding FOSS, the regression analysis shows a positive correlation between FOSS and the organization's integration and learning capabilities. At the same time, it rejected the positive correlation between FOSS and the organization's reconfiguring capability. When the organization has relatively weak capabilities in reconfiguring current resources and practices, it may fail to respond to innovation effectively. Instead, the organization may facilitate BIM adoption through learning and collaboration with others through their inter-organizational network.

Thirdly, the WSS and RAS are negatively associated with learning capability but not associated with integration capability. These results suggest that although the dynamic capability can affect organizations’ voluntary adoption of BIM, weak learning capability plays the most significant role in the organizations' decision to choose a relatively inactive response strategy. Another unexpected research finding is that the WSS positively correlates with reconfiguring capability. This result could be explained by the unique characteristics of the Hong Kong construction industry, where there is no mandatory requirement for BIM use. Organizations may prefer to investigate the development of the market and assess potential risks and possible benefits of BIM adoption when faced with a changing industry environment.

Lastly, the results from hierarchical regression analysis support both the positive association between social status with PLIS and FOSS, and the negative association with WSS and RAS, respectively. These results provide strong evidence that organizations with a more prominent social status will have a stronger incentive to adopt innovation.

Together with the findings of (Yu Zhou, Hong, Zhu, Yang, & Zhao, 2018), this study suggests that organizations of different social statuses will implement distinct strategic responses to innovation.

6.6 Chapter Summary

Using correlation analysis and hierarchical regression analysis, this chapter has firstly categorized and theorized strategic responses to innovative technology based on BIM adoption practices in the regional construction industry. Further, it has explored the impact of dynamic capability and social status on the choice of the strategic response at the organizational level. The result of correlation analysis demonstrates the diversity of regional organizations in terms of their strategic responses and the variety of factors driving the different strategic responses in the same industry environment. The hierarchical regression analysis results also reveal the association between strategic responses with dynamic capability and social status, respectively.

This chapter has contributed to the study of why organizations in the construction industry have varying levels of new technology adoption in the same external environment by conceptualizing and quantifying the organization's dynamic capabilities and social status. The construction industry in Hong Kong is a relatively open market, and within this regional market there are differences among organizations regarding their maturity and depth of the BIM implementation practice. This study helps to understand the complex innovation implementation process and provides managerial and practical implications.

CHAPTER 7 CONCLUSION

7.1 Introduction

This chapter concluded the whole thesis. The research objectives are firstly reviewed together the outcomes of each objective are presented. The major research findings, as well as the research contributions, are also highlighted. This chapter also listed the research limitations and the suggestion for further research.

7.2 Review and Related Outcomes of Research Objectives

As listed in the research aim and objectives section, this study has proposed three research objectives to model the structure of collaborative networks of BIM implementation systematically and to explore the organizational strategic response to innovation based on the BIM implementation practice in the Hong Kong construction industry.

The specific objectives and related research outcomes achieved in Chapter 4-6 are summarized as follows:

Objective 1: To categorize and compare the structural characteristics of project-based collaborative networks in terms of different types of construction projects for BIM implementation in Hong Kong

Outcomes: Chapter 4 has categorized the BIM collaboration networks based on project types, and analyzed and compared the evolution process of collaborative networks of different project types from a network perspective.

Objective 2: To empirically model the evolution of the industry-level network of project-based collaborative relationships in Hong Kong for BIM implementation over time and further explore how this evolution is influenced by a set of micro-mechanisms

Outcomes: Chapter 5 has characterized the evolution of the macro-structure of the project-based collaborative network for BIM implementation in the regional construction industry and explored the underlying factors which drive this complex adaptive system.

Objective 3: To investigate and assess the impacts of dynamic capabilities and social status on the innovation strategic response from an organizational level based on the implementation practices of BIM in the Hong Kong construction industry

Outcomes: Chapter 6 has categorized and theorized strategic response to innovative technology based on the BIM adoption practices in the regional construction industry and explored the impact of dynamic capability and social status on the choice of the strategic response on the organizational level.

7.3 Summary of Major Research Findings

Based on the longitudinal data on 192 BIM-based construction projects (involving a total of 204 owners, design consultants, and main contractors) conducted in Hong Kong during 2008-2017, as well as the methods of stochastic actor-oriented models (SAOM) and hierarchical regressions, the research has provided a comprehensive study on the adoption of BIM in the regional construction industry from a network perspective. The major findings of this research are as follows.

(1) Descriptive analyses of the project-based collaborative network for BIM implementation among the 204 investigated organizations reveal that the network becomes increasingly dense over time but is persistently characterized with small-world properties, including relatively short path lengths among network nodes and high clustering coefficient. This analysis also suggests that the evolution process of networks expands around a small number of nodes. Therefore, some prominent organizations consistently occupied the relatively important position in the core-periphery structure, helping facilitate the diffusion of BIM-related knowledge in the Hong Kong construction industry over time. A comparison of the project-based collaborative networks for BIM implementation in the residential project (RPCN), transportation project (TPCN), and other projects (OPCN) in the Hong Kong construction industry further reveals that the evolution of network structure differs in the type of project. The role and influence of organizations with different types and attributes in the three kinds of networks also varies.

(2) With regard to the micro-mechanisms underlying the dynamics of the project-based collaborative network, the results of SAOM analysis provide evidence that the evolution of the macro-level network significantly relates to the structure-based preferential attachment effect and the experience-based similarity effect operating at the micro-level. It is also revealed that the individual covariate effects related to organizational ownership type and organizational BIM experience also significantly influence the dynamics of the project-based collaborative network. Furthermore, the result also indicates that the project owners do not tend substantially to select design consultants and main contractors with similar types of organizational ownership as their project partners with more frequency in BIM-based projects in Hong Kong.

(3) The correlation analysis result provides evidence that the dynamic capability and social status of organizations in the regional construction industry has a significant difference and further results in the different accept levels of BIM. After categorizing and theorizing strategic response to innovative technology into four specified items, the hierarchical regression results also highlight the impact of dynamic capability and social status on strategic response to BIM.

7.4 Research Contributions

The findings of this thesis also have several managerial and policy implications. Firstly, the empirical findings reveal that there is a tendency for project-based collaborative networks among industry organizations to expand around a small number of “star” nodes, and that the preferential attachment effect (which reflects the success-breeds-success tendency) generally plays an important role in influencing the organizational competitiveness and network positions of industry organizations. This finding tends to suggest the significant value of social capital, which is related to knowledge learning, information access and capability signaling, embedded in project-based collaborative networks in the construction. As such, when facing changes in technology or market environments, it is advisable for design and construction firms to employ first-mover strategies to possess advantaged network positions in the industry and therefore gain long-term organizational competitiveness.

Secondly, the findings also provide evidence that the covariate similarity effect related to BIM experience significantly influences the formation of project-based collaborative networks among owners and designers/contractors. Due to the importance of project-based collaborative ties for the diffusion of knowledge and innovations among organizations in the construction industry, this homophily tendency may generate separations among industry organizations and hamper the transfer of knowledge related to innovative technologies like BIM from experienced organizations to less experienced organizations. In order to mitigate the negative influence of this tendency, government agencies could take specific measures to foster communication among different levels of organizations and thus facilitate the diffusion of related technological knowledge throughout the industry.

Thirdly, the covariate-alter effect related to organizational ownership type is revealed to be not statistically significant, suggesting that, compared with overseas enterprises, local design and construction enterprises have no obvious advantage in bidding for new design and construction contracts in BIM-based projects in Hong Kong. The significant covariate-alter effect related to organizational BIM experience tends to further suggest that an important reason for this result is related to the difference in BIM experience between local and overseas firms. When taking measures to facilitate the development of BIM in the regional construction industry, therefore, government agencies should pay special attention to fostering the BIM capabilities of local design and construction firms and improving their overall competitiveness in the industry.

Lastly, the diverse dynamic capability and uneven social status of organizations in the regional construction industry result in different response strategies to BIM adoption. The findings suggest that higher dynamic capabilities and leading social status drive organizations to develop more aggressive response strategies. Given the potential benefits of BIM implementation and the low adoption rate in Hong Kong, the government or managers could formulate specific incentivization policies and training programs for organizations with weak dynamic capacity and on the edge of collaborative networks to improve their competitiveness in the domain of BIM implementation, further promote the proliferation of BIM in the region.

7.5 Limitations and Future Research Directions

This study has several limitations that provide opportunities for future research. First, the empirical data used in this study was collected within the specific institutional and cultural context of the Hong Kong construction industry, where the development of BIM has been primarily driven by the market itself during the past decade. This may limit the generalizability of the empirical results on network dynamics to other institutional and cultural contexts. Future research could collect larger scale data in more diversified institutional and cultural contexts to further validate or expand the findings presented in this study.

Secondly, limited by the availability of empirical data as well as the data processing capability of extant network dynamics models (Snijders et al., 2010), this empirical study has only examined the project-based collaborative networks among the following three types of organizations: owners, design consultants, and main contractors. And similarly, limited by the sample of empirical data, this study categorizes all projects other than residential and transportation as other projects. In order to provide a more comprehensive comparison of the different kinds of BIM-based projects and provide a more comprehensive understanding of how different types of organizations interact with each other in BIM implementation practices across projects. Future research could attempt to include more types of organizations and projects, such as consultants and subcontractors, and commercial projects and industrial projects, when modeling project-based collaborative networks in the construction industry.

Third, constrained by the availability of empirical data, when examining the dynamics of project-based collaborative networks for BIM implementation, this study has focused on assessing the influences of the structure-based preferential attachment effect as well as the dyadic (i.e., the similarity effects) and individual covariate effects related to organizational ownership type and BIM experience. Future research could attempt to further assess the influence of the attribute-based effects related to other types of organizational attributes (e.g., organizational capability, organizational size and organizational culture) to more comprehensively model the dynamics of project-based collaborative networks.

7.6 Chapter Summary

This chapter reviewed the initially proposed objectives and summarized the major research findings of the thesis. Then the research contributions are well demonstrated. The limitations and future research directions are listed at the end of this thesis.

References

Abbasi, A., Wigand, R. T., & Hossain, L. (2014). Measuring social capital through network analysis and its influence on individual performance. *Library & Information Science Research, 36*(1), 66-73.

Abd Jamil, A. H., & Fathi, M. S. (2018). Contractual challenges for BIM-based construction projects: a systematic review. *Built Environment Project and Asset Management, 8*(4), 372-385. Retrieved from <Go to ISI>://WOS:000444550200004. doi:10.1108/bepam-12-2017-0131

Abubakar, A. M., Elrehail, H., Alatailat, M. A., & Elçi, A. (2019). Knowledge management, decision-making style and organizational performance. *Journal of Innovation & Knowledge, 4*(2), 104-114.

Adams, R., Bessant, J., & Phelps, R. (2006). Innovation management measurement: A review. *International journal of management reviews, 8*(1), 21-47.

Agenda, I. (2016). *Shaping the future of construction a breakthrough in mindset and technology*. Paper presented at the World Economic Forum.

Agostini, L., & Nosella, A. (2019). Inter-organizational relationships involving SMEs: A bibliographic investigation into the state of the art. *Long Range Planning, 52*(1), 1-31.

Ahuja, R., Sawhney, A., Jain, M., Arif, M., & Rakshit, S. (2020). Factors influencing BIM adoption in emerging markets - the case of India. *International Journal of Construction Management, 20*(1), 65-76. Retrieved from <Go to ISI>://WOS:000489606700006. doi:10.1080/15623599.2018.1462445

Ainuddin, R. A., Beamish, P. W., Hulland, J. S., & Rouse, M. J. (2007). Resource attributes and firm performance in international joint ventures. *Journal of World Business, 42*(1), 47-60.

Akinade, O. O., Oyedele, L. O., Ajayi, S. O., Bilal, M., Alaka, H. A., Owolabi, H. A., & Arawomo, O. O. (2018). Designing out construction waste using BIM technology: Stakeholders' expectations for industry deployment. *Journal of Cleaner Production, 180*, 375-385. Retrieved from <Go to ISI>://WOS:000427218700034. doi:10.1016/j.jclepro.2018.01.022

Al Hattab, M., & Hamzeh, F. (2015). Using social network theory and simulation to compare traditional versus BIM–lean practice for design error management. *Automation in Construction, 52*, 59-69.

Alexander, M. (2003). Local policies toward migrants as an expression of Host-Stranger relations: A proposed typology. *Journal of ethnic and migration studies, 29*(3), 411-430.

Alinaitwe, H., Apolot, R., & Tindiwensi, D. (2013). Investigation into the causes of delays and cost overruns in Uganda's public sector construction projects. *Journal of Construction in Developing Countries, 18*(2), 33.

Alreshidi, E., Mourshed, M., & Rezgui, Y. (2017). Factors for effective BIM governance. *Journal of Building Engineering, 10*, 89-101.

Alsamadani, R., Hallowell, M. R., Javernick-Will, A., & Cabello, J. (2013). Relationships among language proficiency, communication patterns, and safety performance in small work crews in the United States. *Journal of Construction Engineering and Management, 139*(9), 1125-1134.

Alwan, Z., Jones, P., & Holgate, P. (2017). Strategic sustainable development in the UK construction industry, through the framework for strategic sustainable development, using Building Information Modelling. *Journal of cleaner production, 140*, 349-358.

Alwisy, A., Hamdan, S. B., Barkokebas, B., Bouferguene, A., & Al-Hussein, M. (2019). A BIM-based automation of design and drafting for manufacturing of wood panels for modular residential buildings. *International Journal of Construction Management, 19*(3), 187-205. Retrieved from <Go to ISI>://WOS:000459462600001. doi:10.1080/15623599.2017.1411458

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic management journal, 14*(1), 33-46.

Anheier, H. K., Gerhards, J., & Romo, F. P. (1995). Forms of capital and social structure in cultural fields: Examining Bourdieu's social topography. *American journal of sociology, 100*(4), 859-903.

Ankney, K. R., & Hidding, G. J. (2005). Fast-Follower Advantages and Network Externalities in IT-Driven Markets. *Journal of Information Science & Technology, 2*(2).

Antwi-Afari, M. F., Li, H., Parn, E. A., & Ewards, D. J. (2018). Critical success factors for implementing building information modelling (BIM): A longitudinal review. *Automation in Construction, 91*, 100-110. Retrieved from <Go to ISI>://WOS:000431470100009. doi:10.1016/j.autcon.2018.03.010

Assink, M. (2006). Inhibitors of disruptive innovation capability: a conceptual model. *European journal of innovation management*.

Bakar, L. J. A., & Ahmad, H. (2010). Assessing the relationship between firm resources and product innovation performance: A resource-based view. *Business Process Management Journal*.

Balland, P.-A. (2012). Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry. *Regional Studies, 46*(6), 741-756.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*(5439), 509-512.

Barney, J. B. (1986). Types of competition and the theory of strategy: Toward an integrative framework. *Academy of management review, 11*(4), 791-800.

Barney, J. B. (1995). Looking inside for competitive advantage. *Academy of Management Perspectives, 9*(4), 49-61.

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. *Journal of management, 36*(1), 256-280.

Barringer, B. R., & Bluedorn, A. C. (1999). The relationship between corporate entrepreneurship and strategic management. *Strategic management journal, 20*(5), 421-444.

Bartsch, V., Ebers, M., & Maurer, I. (2013). Learning in project-based organizations: The role of project teams' social capital for overcoming barriers to learning. *International Journal of Project Management, 31*(2), 239-251.

Baum, J. A., & Ingram, P. (2002). Interorganizational learning and network organization: Toward a behavioral theory of the interfirm. *The economics of choice, change, and organization: Essays in memory of Richard M. Cyert*, 191-218.

Becerik-Gerber, B., Jazizadeh, F., Li, N., & Calis, G. (2012). Application areas and data requirements for BIM-enabled facilities management. *Journal of Construction Engineering and Management, 138*(3), 431-442.

Beckert, J. (2009). The great transformation of embeddedness: Karl Polanyi and the new economic sociology. *Beckert Jens*, 38-55.

Beerepoot, M., & Beerepoot, N. (2007). Government regulation as an impetus for innovation: Evidence from energy performance regulation in the Dutch residential building sector. *Energy Policy, 35*(10), 4812-4825.

Behera, P., Mohanty, R., & Prakash, A. (2015). Understanding construction supply chain management. *Production Planning & Control, 26*(16), 1332-1350.

Blayse, A. M., & Manley, K. (2004). Key influences on construction innovation. *Construction Innovation, 4*(3), 143-154.

Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social networks, 29*(4), 555-564.

Borgatti, S. P., & Everett, M. G. (2000). Models of core/periphery structures. *Social networks, 21*(4), 375-395.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science, 323*(5916), 892-895.

Bossink, B. A. (2004). Managing drivers of innovation in construction networks. *Journal of Construction Engineering and Management, 130*(3), 337-345.

Bossle, M. B., de Barcellos, M. D., Vieira, L. M., & Sauvée, L. (2016). The drivers for adoption of eco-innovation. *Journal of cleaner production, 113*, 861-872.

Bowman, C., & Ambrosini, V. (2000). Value creation versus value capture: towards a coherent definition of value in strategy. *British journal of management, 11*(1), 1-15.

Bowman, C., & Ambrosini, V. (2010). How value is created, captured and destroyed. *European business review*.

Brady, T., & Davies, A. (2004). Building project capabilities: from exploratory to exploitative learning. *Organization studies, 25*(9), 1601-1621.

Broekel, T., Balland, P.-A., Burger, M., & van Oort, F. (2014). Modeling knowledge networks in economic geography: a discussion of four methods. *The annals of regional science, 53*(2), 423-452.

Brouwer, R., Barton, D., Bateman, I., Brander, L., Georgiou, S., Martín-Ortega, J., . . . Wagtendonk, A. (2009). Economic valuation of environmental and resource costs and benefits in the water framework directive: technical guidelines for practitioners. *Institute for Environmental Studies, VU University Amsterdam, the Netherlands*.

Brunswicker, S., & Vanhaverbeke, W. (2015). Open innovation in small and medium-sized enterprises (SMEs): External knowledge sourcing strategies and internal organizational facilitators. *Journal of small business management, 53*(4), 1241-1263.

Bryde, D., Broquetas, M., & Volm, J. M. (2013). The project benefits of building information modelling (BIM). *International Journal of Project Management, 31*(7), 971-980.

Burt, R. S. (2000). The network structure of social capital. *Research in Organizational behavior, 22*, 345-423.

Burt, R. S. (2002). The social capital of structural holes. *The new economic sociology: Developments in an emerging field, 148*(90), 122.

Cao, D., Li, H., & Wang, G. (2014). Impacts of isomorphic pressures on BIM adoption in construction projects. *Journal of Construction Engineering and Management, 140*(12), 04014056.

Cao, D., Li, H., Wang, G., Luo, X., & Tan, D. (2018). Relationship network structure and organizational competitiveness: Evidence from BIM implementation practices in the construction industry. *Journal of Management in Engineering, 34*(3), 04018005.

Cao, D., Li, H., Wang, G., Luo, X., Yang, X., & Tan, D. (2017). Dynamics of project-based collaborative networks for BIM implementation: Analysis based on stochastic actor-oriented models. *Journal of Management in Engineering, 33*(3), 04016055.

Cao, D., Wang, G., Li, H., Skitmore, M., Huang, T., & Zhang, W. (2015). Practices and effectiveness of building information modelling in construction projects in China. *Automation in Construction, 49*, 113-122.

Cao, D. P., Li, H., & Wang, G. B. (2017). Impacts of building information modeling (BIM) implementation on design and construction performance: a resource dependence theory perspective. *Frontiers of Engineering Management, 4*(1), 20-34. Retrieved from <Go to ISI>://WOS:000408058600003. doi:10.15302/j-fem-2017010

Cao, D. P., Li, H., Wang, G. B., & Huang, T. (2017). Identifying and contextualising the motivations for BIM implementation in construction projects: An empirical study in China. *International Journal of Project Management,* *35*(4), 658-669. Retrieved from <Go to ISI>://WOS:000399862900010. doi:10.1016/j.ijproman.2016.02.002

Cao, D. P., Li, H., Wang, G. B., Luo, X. C., & Tan, D. (2018). Relationship Network Structure and Organizational Competitiveness: Evidence from BIM Implementation Practices in the Construction Industry. *Journal of Management in Engineering, 34*(3), 12. Retrieved from <Go to ISI>://WOS:000427961900006. doi:10.1061/(asce)me.1943-5479.0000600

Cao, D. P., Li, H., Wang, G. B., Luo, X. C., Yang, X. C., & Tan, D. (2017). Dynamics of Project-Based Collaborative Networks for BIM Implementation: Analysis Based on Stochastic Actor-Oriented Models. *Journal of Management in Engineering, 33*(3), 12. Retrieved from <Go to ISI>://WOS:000398537700012. doi:10.1061/(asce)me.1943-5479.0000503

Cao, D. P., Li, H., Wang, G. B., & Zhang, W. J. (2016). Linking the Motivations and Practices of Design Organizations to Implement Building Information Modeling in Construction Projects: Empirical Study in China. *Journal of Management in Engineering, 32*(6), 10. Retrieved from <Go to ISI>://WOS:000386361800005. doi:10.1061/(asce)me.1943-5479.0000453

Carneiro, A. (2000). How does knowledge management influence innovation and competitiveness? *Journal of Knowledge Management*.

Chan, D. W., Olawumi, T. O., & Ho, A. M. (2019). Perceived benefits of and barriers to Building Information Modelling (BIM) implementation in construction: The case of Hong Kong. *Journal of Building Engineering, 25*, 100764.

Chan, D. W. M., Olawumi, T. O., & Ho, A. M. L. (2019). Perceived benefits of and barriers to Building Information Modelling (BIM) implementation in construction: The case of Hong Kong. *Journal of Building Engineering, 25*, 10. Retrieved from <Go to ISI>://WOS:000477702200004. doi:10.1016/j.jobe.2019.100764

Chang, C.-H. (2011). The influence of corporate environmental ethics on competitive advantage: The mediation role of green innovation. *Journal of Business Ethics, 104*(3), 361-370.

Chang, C. Y., Pan, W. J., & Howard, R. (2017). Impact of Building Information Modeling Implementation on the Acceptance of Integrated Delivery Systems: Structural Equation Modeling Analysis. *Journal of Construction Engineering* *and Management, 143*(8), 04017044. Retrieved from <Go to ISI>://WOS:000403723700017. doi:10.1061/(asce)co.1943-7862.0001335

Chege, S. M., & Wang, D. (2020). The impact of entrepreneurs' environmental analysis strategy on organizational performance. *Journal of Rural Studies, 77*, 113-125.

Chen, K., Lu, W. S., Xue, F., Tang, P. B., & Li, L. H. (2018). Automatic building building information model reconstruction in high-density urban areas: Augmenting multi-source data with architectural knowledge. *Automation in Construction, 93*, 22-34. Retrieved from <Go to ISI>://WOS:000441687500003. doi:10.1016/j.autcon.2018.05.009

Cheng, J. C., & Lu, Q. (2015). A review of the efforts and roles of the public sector for BIM adoption worldwide. *Journal of Information Technology in Construction (ITcon), 20*(27), 442-478.

Cheng, J. C. P., & Lu, Q. Q. (2015). A review of the efforts and roles of the public sector for BIM adoption worldwide. *Journal of Information Technology in Construction, 20*, 442-478. Retrieved from <Go to ISI>://WOS:000384838700006.

Chiang, Y.-H., Tang, B.-S., & Leung, W.-Y. (2001). Market structure of the construction industry in Hong Kong. *Construction management and economics, 19*(7), 675-687.

Chinowsky, P., Diekmann, J., & Galotti, V. (2008). Social network model of construction. *Journal of Construction Engineering and Management, 134*(10), 804-812.

Chinowsky, P., & Taylor, J. E. (2012). Networks in engineering: an emerging approach to project organization studies. *Engineering Project Organization Journal, 2*(1-2), 15-26.

Chiu, C.-M., Hsu, M.-H., & Wang, E. T. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision support systems, 42*(3), 1872-1888.

Chong, H.-Y., Lee, C.-Y., & Wang, X. (2017). A mixed review of the adoption of Building Information Modelling (BIM) for sustainability. *Journal of cleaner production, 142*, 4114-4126.

Chowdhury, A. N., Chen, P. H., & Tiong, R. L. (2011). Analysing the structure of public–private partnership projects using network theory. *Construction management and economics, 29*(3), 247-260.

Chowdhury, M. M. H., & Quaddus, M. (2017). Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *International Journal of Production Economics, 188,* 185-204.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly*, 128-152.

Colbert, B. A. (2004). The complex resource-based view: Implications for theory and practice in strategic human resource management. *Academy of management review, 29*(3), 341-358.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *psychometrika, 16*(3), 297-334.

Damanpour, F., Walker, R. M., & Avellaneda, C. N. (2009). Combinative effects of innovation types and organizational performance: A longitudinal study of service organizations. *Journal of Management Studies, 46*(4), 650-675.

Dave, B., & Koskela, L. (2009). Collaborative knowledge management—A construction case study. *Automation in Construction, 18*(7), 894-902.

de Vries, H. J., & Verhagen, W. P. (2016). Impact of changes in regulatory performance standards on innovation: A case of energy performance standards for newly-built houses. *Technovation, 48,* 56-68.

Dess, G. G., Ireland, R. D., Zahra, S. A., Floyd, S. W., Janney, J. J., & Lane, P. J. (2003). Emerging issues in corporate entrepreneurship. *Journal of management, 29*(3), 351-378.

Di Vincenzo, F., & Mascia, D. (2012). Social capital in project-based organizations: Its role, structure, and impact on project performance. *International Journal of Project Management, 30*(1), 5-14.

Dibrell, C., Craig, J. B., & Neubaum, D. O. (2014). Linking the formal strategic planning process, planning flexibility, and innovativeness to firm performance. *Journal of Business Research, 67*(9), 2000-2007.

Ding, L. Y., & Xu, X. (2014). Application of Cloud Storage on BIM Life-cycle Management. *International Journal of Advanced Robotic Systems, 11*. Retrieved from <Go to ISI>://WOS:000341371000001. doi:10.5772/58443

Ding, L. Y., Zhou, Y., & Akinci, B. (2014). Building Information Modeling (BIM) application framework: The process of expanding from 3D to computable nD. *Automation in Construction, 46,* 82-93. Retrieved from <Go to ISI>://WOS:000341478500010. doi:10.1016/j.autcon.2014.04.009

Ding, Z., Liu, S., Liao, L., & Zhang, L. (2019). A digital construction framework integrating building information modeling and reverse engineering technologies for renovation projects. *Automation in Construction, 102*, 45-58.

Ding, Z. K., Zuo, J., Wu, J. C., & Wang, J. Y. (2015). Key factors for the BIM adoption by architects: a China study. *Engineering Construction and Architectural Management, 22*(6), 732-748. Retrieved from <Go to ISI>://WOS:000369434200008. doi:10.1108/ecam-04-2015-0053

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., . . . Leitão, P. J. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*(1), 27-46.

Dossick, C. S., & Neff, G. (2010). Organizational divisions in BIM-enabled commercial construction. *Journal of Construction Engineering and Management, 136*(4), 459-467.

Dubois, A., & Gadde, L.-E. (2002). The construction industry as a loosely coupled system: implications for productivity and innovation. *Construction management & economics, 20*(7), 621-631.

Dulaimi, M. F., Y. Ling, F. Y., Ofori, G., & Silva, N. D. (2002). Enhancing integration and innovation in construction. *Building research & information, 30*(4), 237-247.

Eastman, C. M., Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2011). *BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors*: John Wiley & Sons.

Egbu, C. O. (2004). Managing knowledge and intellectual capital for improved organizational innovations in the construction industry: an examination of critical success factors. *Engineering, Construction and Architectural Management*.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic management journal, 21*(10-11), 1105-1121.

El-Sheikh, A., & Pryke, S. D. (2010). Network gaps and project success. *Construction management and economics, 28*(12), 1205-1217.

Eleftheriadis, S., Mumovic, D., & Greening, P. (2017). Life cycle energy efficiency in building structures: A review of current developments and future outlooks based on BIM capabilities. *Renewable & Sustainable Energy Reviews, 67*, 811-825. Retrieved from <Go to ISI>://WOS:000389088900059. doi:10.1016/j.rser.2016.09.028

Encaoua, D., Guellec, D., & Martínez, C. (2006). Patent systems for encouraging innovation: Lessons from economic analysis. *Research Policy, 35*(9), 1423-1440.

Enshassi, A., Ayyash, A., & Choudhry, R. M. (2016). BIM for construction safety improvement in Gaza strip: awareness, applications and barriers. *International Journal of Construction Management, 16*(3), 249-265. Retrieved from <Go to ISI>://WOS:000381692000006. doi:10.1080/15623599.2016.1167367

Fagerholt, K., Christiansen, M., Hvattum, L. M., Johnsen, T. A., & Vabø, T. J. (2010). A decision support methodology for strategic planning in maritime transportation. *Omega, 38*(6), 465-474.

Fan, S. L. (2014). Intellectual Property Rights in Building Information Modeling Application in Taiwan. *Journal of Construction Engineering and Management, 140*(3), 04013058. Retrieved from <Go to ISI>://WOS:000332659900015. doi:10.1061/(asce)co.1943-7862.0000808

Feldman, M. S. (2000). Organizational routines as a source of continuous change. *Organization science, 11*(6), 611-629.

Feldman, M. S., & Pentland, B. T. (2003). Reconceptualizing organizational routines as a source of flexibility and change. *Administrative science quarterly, 48*(1), 94-118.

Flap, H. (2002). No man is an island: the research programme of a social capital theory. *Conventions and Structures in Economic Organisations: Markets and Hierarchies. Cheltenham: Edward Elgar*.

Ford, C. M. (1996). A theory of individual creative action in multiple social domains. *Academy of management review, 21*(4), 1112-1142.

Ford, C. M., & Gioia, D. A. (2000). Factors influencing creativity in the domain of managerial decision making. *Journal of management, 26*(4), 705-732.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing*

Research, 18(1), 39-50. Retrieved from http://www.jstor.org/stable/3151312. doi:10.2307/3151312

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social networks, 1*(3), 215-239.

Froese, T. M. (2010). The impact of emerging information technology on project management for construction. *Automation in Construction, 19*(5), 531-538.

Fullerton, R. R., Kennedy, F. A., & Widener, S. K. (2014). Lean manufacturing and firm performance: The incremental contribution of lean management accounting practices. *Journal of Operations Management, 32*(7-8), 414-428.

Gann, D. M., & Salter, A. J. (2000). Innovation in project-based, service-enhanced firms: the construction of complex products and systems. *Research Policy, 29*(7-8), 955-972.

Gao, J., & Fischer, M. (2008). *Framework and case studies comparing implementations and impacts of 3D/4D modeling across projects.* Stanford University Stanford,

Ghaffarianhoseini, A., Tookey, J., Ghaffarianhoseini, A., Naismith, N., Azhar, S., Efimova, O., & Raahemifar, K. (2017). Building Information Modelling (BIM) uptake: Clear benefits, understanding its implementation, risks and challenges. *Renewable & Sustainable Energy Reviews, 75*, 1046-1053. Retrieved from <Go to ISI>://WOS:000401395000084. doi:10.1016/j.rser.2016.11.083

Giel, B. K., & Issa, R. R. (2013). Return on investment analysis of using building information modeling in construction. *Journal of Computing in Civil Engineering, 27*(5), 511-521.

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of economic perspectives, 19*(1), 33-50.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology, 78*(6), 1360-1380.

Gu, N., & London, K. (2010). Understanding and facilitating BIM adoption in the AEC industry. *Automation in Construction, 19*(8), 988-999. Retrieved from <Go to ISI>://WOS:000285223900003. doi:10.1016/j.autcon.2010.09.002

Guevara, J., Salazar, J., & Garvin, M. J. (2020). Social network analysis of road PPP equity markets in Canada, Chile, and the United States. *Journal of Management in Engineering, 36*(5), 04020058.

Han, Y., Li, Y., Taylor, J. E., & Zhong, J. (2018). Characteristics and evolution of innovative collaboration networks in architecture, engineering, and construction: Study of national prize-winning projects in China. *Journal of Construction Engineering and Management, 144*(6), 04018038.

Hanaki, N., Nakajima, R., & Ogura, Y. (2010). The dynamics of R&D network in the IT industry. *Research Policy, 39*(3), 386-399.

Hanneman, R. A., & Riddle, M. (2005). Introduction to social network methods. In: University of California Riverside.

Hargadon, A. B. (2002). Brokering knowledge: Linking learning and innovation. *Research in Organizational behavior, 24*, 41-85.

Hartmann, A. (2006). The role of organizational culture in motivating innovative behaviour in construction firms. *Construction Innovation, 6*(3), 159-172.

Hartmann, T., Gao, J., & Fischer, M. (2008). Areas of application for 3D and 4D models on construction projects. *Journal of Construction Engineering and Management, 134*(10), 776-785.

Hatem, W. A., Abd, A. M., & Abbas, N. N. (2018). Motivation Factors for Adopting Building Information Modeling (BIM) in Iraq. *Engineering Technology & Applied Science Research, 8*(2), 2668-2672. Retrieved from <Go to ISI>://WOS:000430563900008.

Hemphälä, J., & Magnusson, M. (2012). Networks for innovation–but what networks and what innovation? *Creativity and innovation management, 21*(1), 3-16.

Heravi, A., Coffey, V., & Trigunarsyah, B. (2015). Evaluating the level of stakeholder involvement during the project planning processes of building projects. *International Journal of Project Management, 33*(5), 985-997.

Hill, M. (2008). Building information modeling (BIM), Transforming design and construction to achieve greater industry productivity. SmartMarket Report: Design and Construction Intelligence. In: McGraw Hill Construction.

Hobday, M. (2000). The project-based organisation: an ideal form for managing complex products and systems? *Research Policy, 29*(7-8), 871-893.

Hossain, M. A., Abbott, E. L. S., Chua, D. K. H., Nguyen, T. Q., & Goh, Y. M. (2018). Design-for-Safety knowledge library for BIM-integrated safety risk reviews. *Automation in Construction, 94*, 290-302. Retrieved from http://www.sciencedirect.com/science/article/pii/S0926580518300840. doi:https://doi.org/10.1016/j.autcon.2018.07.010

Howard, R., Restrepo, L., & Chang, C. Y. (2017). Addressing individual perceptions: An application of the unified theory of acceptance and use of technology to building information modelling. *International Journal of Project Management, 35*(2), 107-120. Retrieved from <Go to ISI>://WOS:000392039400002. doi:10.1016/j.ijproman.2016.10.012

Hughes, C., Swaminathan, V., & Brooks, G. (2019). Driving brand engagement through online social influencers: An empirical investigation of sponsored blogging campaigns. *Journal of Marketing, 83*(5), 78-96.

Hughes, P., & Morgan, R. E. (2008). Fitting strategic resources with product-market strategy: performance implications. *Journal of Business Research, 61*(4), 323-331.

Humphreys, P., Matthews, J., & Kumaraswamy, M. (2003). Pre-construction project partnering: from adversarial to collaborative relationships. *Supply Chain Management: An International Journal*.

Irwin, J. G., Hoffman, J. J., & Lamont, B. T. (1998). The effect of the acquisition of technological innovations on organizational performance: A resource-based view. *Journal of Engineering and Technology Management, 15*(1), 25-54.

Jackson, S. E., Joshi, A., & Erhardt, N. L. (2003). Recent research on team and organizational diversity: SWOT analysis and implications. *Journal of management, 29*(6), 801-830.

Jay, J. (2013). Navigating paradox as a mechanism of change and innovation in hybrid organizations. *Academy of Management journal, 56*(1), 137-159.

Jensen, P. A., & Jóhannesson, E. I. (2013). Building information modelling in Denmark and Iceland. *Engineering, Construction and Architectural Management*.

Jiang, W., Chai, H., Shao, J., & Feng, T. (2018). Green entrepreneurial orientation for enhancing firm performance: A dynamic capability perspective. *Journal of cleaner production, 198*, 1311-1323.

Jin, R., Hancock, C., Tang, L., Chen, C., Wanatowski, D., & Yang, L. (2017). Empirical study of BIM implementation–based perceptions among Chinese practitioners. *Journal of Management in Engineering, 33*(5), 04017025.

Jin, R., Li, B., Zhou, T., Wanatowski, D., & Piroozfar, P. (2017). An empirical study of perceptions towards construction and demolition waste recycling and reuse in China. *Resources, Conservation and Recycling, 126,* 86-98.

Jin, R. Y., Hancock, C., Tang, L., Chen, C., Wanatowski, D., & Yang, L. (2017). Empirical Study of BIM Implementation-Based Perceptions among Chinese Practitioners. *Journal of Management in Engineering, 33*(5). Retrieved from <Go to ISI>://WOS:000407337700009. doi:10.1061/(asce)me.1943-5479.0000538

Jóhannesson, E. I. (2009). Implementation of BIM. *DTU Management Engineering*.

Jung, Y., Chin, S., & Kim, K. (2004). Informatization index for the construction industry. *Journal of Computing in Civil Engineering, 18*(3), 267-276. Retrieved from <Go to ISI>://WOS:000222276100010. doi:10.1061/(asce)0887-3801(2004)18:3(267)

Kabirifar, K., & Mojtahedi, M. (2019). The impact of Engineering, Procurement and Construction (EPC) phases on project performance: A case of large-scale residential construction project. *Buildings, 9*(1), 15.

Kamara, J. M., Augenbroe, G., Anumba, C. J., & Carrillo, P. M. (2002). Knowledge management in the architecture, engineering and construction industry. *Construction Innovation*.

Kamboj, S., & Rana, S. (2021). Big data-driven supply chain and performance: a resource-based view. *The TQM Journal*.

Katsoulakos, T., & Katsoulacos, Y. (2007). Integrating corporate responsibility principles and stakeholder approaches into mainstream strategy: a stakeholder-oriented and integrative strategic management framework. *Corporate Governance: The international journal of business in society*.

Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First-mover advantage: A synthesis, conceptual framework, and research propositions. *Journal of Marketing, 56*(4), 33-52.

Kim, K., & Teizer, J. (2014). Automatic design and planning of scaffolding systems using building information modeling. *Advanced Engineering Informatics, 28*(1), 66-80. Retrieved from <Go to ISI>://WOS:000332357100006. doi:10.1016/j.aei.2013.12.002

Kirner, E., Kinkel, S., & Jaeger, A. (2009). Innovation paths and the innovation performance of low-technology firms—An empirical analysis of German industry. *Research Policy, 38*(3), 447-458.

Klingebiel, R., & Joseph, J. (2016). Entry timing and innovation strategy in feature phones. *Strategic management journal, 37*(6), 1002-1020.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science, 3*(3), 383-397.

Kryscynski, D., Coff, R., & Campbell, B. (2021). Charting a path between firm-specific incentives and human capital-based competitive advantage. *Strategic management journal, 42*(2), 386-412.

Kubba, S. (2012). *Handbook of green building design and construction: LEED, BREEAM, and Green Globes*: Butterworth-Heinemann.

Kuhlman, T., & Farrington, J. (2010). What is sustainability? *Sustainability, 2*(11), 3436-3448.

Kwak, D.-W., Seo, Y.-J., & Mason, R. (2018). Investigating the relationship between supply chain innovation, risk management capabilities and competitive advantage in global supply chains. *International Journal of Operations & Production Management*.

Langley, A. (1988). The roles of formal strategic planning. *Long Range Planning, 21*(3), 40-50.

Lau, A. K., & Lo, W. (2019). Absorptive capacity, technological innovation capability and innovation performance: An empirical study in Hong Kong. *International Journal of Technology Management, 80*(1-2), 107-148.

Lau, T., Wong, Y., Chan, K., & Law, M. (2001). Information technology and the work environment–does IT change the way people interact at work? *Human systems management, 20*(3), 267-279.

Lavie, D., Lechner, C., & Singh, H. (2007). The performance implications of timing of entry and involvement in multipartner alliances. *Academy of Management journal, 50*(3), 578-604.

Lawrence, P. R., & Dyer, D. (1983). *Renewing american industry*: New York: Free Press; London: Collier Macmillan Publishers.

Lee, G., Park, H. K., & Won, J. (2012). D3 City project—Economic impact of BIM-assisted design validation. *Automation in Construction, 22*, 577-586.

Lee, J., & Bonk, C. J. (2016). Social network analysis of peer relationships and online interactions in a blended class using blogs. *The Internet and Higher Education, 28,* 35-44.

Lee, R. P., & Grewal, R. (2004). Strategic responses to new technologies and their impact on firm performance. *Journal of Marketing, 68*(4), 157-171.

Lee, S. I., Bae, J. S., & Cho, Y. S. (2012). Efficiency analysis of Set-based Design with structural building information modeling (S-BIM) on high-rise building structures. *Automation in Construction, 23*, 20-32. Retrieved from <Go to ISI>://WOS:000302670000003. doi:10.1016/j.autcon.2011.12.008

Lee, Y.-S., Kim, J.-J., & Lee, T. S. (2016). Topological competiveness based on social relationships in the Korean construction-management industry. *Journal of Construction Engineering and Management, 142*(11), 05016014.

Lee, Y. C., Solihin, W., & Eastman, C. M. (2019). The Mechanism and Challenges of Validating a Building Information Model regarding data exchange standards. *Automation in Construction, 100*, 118-128. Retrieved from <Go to ISI>://WOS:000457951600009. doi:10.1016/j.autcon.2018.12.025

Leiberman, M. B., & Montgomery, D. B. (2012). First-mover/pioneer strategies. In *Handbook of marketing strategy*: Edward Elgar Publishing.

Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences, 109*(1), 68-72.

Li, C. Z., Zhong, R. Y., Xue, F., Xu, G., Chen, K., Huang, G. G., & Shen, G. Q. (2017). Integrating RFID and BIM technologies for mitigating risks and improving schedule performance of prefabricated house construction. *Journal of Cleaner Production, 165*, 1048-1062. Retrieved from <Go to ISI>://WOS:000411544400090. doi:10.1016/j.jclepro.2017.07.156

Li, H., Lu, W., & Huang, T. (2009). Rethinking project management and exploring virtual design and construction as a potential solution. *Construction management and economics, 27*(4), 363-371.

Li, J., Wang, Y., Wang, X. Y., Luo, H. B., Kang, S. C., Wang, J., . . . Jiao, Y. (2014). Benefits of Building Information Modelling in the Project Lifecycle: Construction Projects in Asia. *International Journal of Advanced Robotic Systems, 11*. Retrieved from <Go to ISI>://WOS:000341369800001. doi:10.5772/58447

Li, J. M., Li, N. P., Peng, J. Q., Cui, H. J., & Wu, Z. B. (2018). A review of currently applied building information modeling tools of constructions in China. *Journal of Cleaner Production, 201*, 358-368. Retrieved from <Go to ISI>://WOS:000445981200031. doi:10.1016/j.jclepro.2018.08.037

Li, L. (2005). The effects of trust and shared vision on inward knowledge transfer in subsidiaries' intra-and inter-organizational relationships. *International business review, 14*(1), 77-95.

Li, X., Wu, P., Shen, G. Q., Wang, X., & Teng, Y. (2017). Mapping the knowledge domains of Building Information Modeling (BIM): A bibliometric approach. *Automation in Construction, 84*, 195-206.

Liao, L., Teo, E. A. L., & Chang, R. (2019). Reducing Critical Hindrances to Building Information Modeling Implementation: The Case of the Singapore Construction Industry. *Applied Sciences, 9*(18), 3833.

Liao, L. H., & Teo, E. A. L. (2017). Critical success factors for enhancing the building information modelling implementation in building projects in Singapore. *Journal of Civil Engineering and Management, 23*(8), 1029-1044. Retrieved from <Go to ISI>://WOS:000419971800006. doi:10.3846/13923730.2017.1374300

Liao, P.-C., Lei, G., Fang, D., & Liu, W. (2014). The relationship between communication and construction safety climate in China. *KSCE Journal of Civil Engineering, 18*(4), 887-897.

Lichtenthaler, U. (2011). Open innovation: Past research, current debates, and future directions. *Academy of Management Perspectives, 25*(1), 75-93.

Lin, N. (2002). *Social capital: A theory of social structure and action* (Vol. 19): Cambridge university press.

Lin, Y., & Wu, L.-Y. (2014). Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. *Journal of Business Research, 67*(3), 407-413.

Lopez, R., Chong, H. Y., Wang, X. Y., & Graham, J. (2016). Technical Review: Analysis and Appraisal of Four-Dimensional Building Information Modeling Usability in Construction and Engineering Projects. *Journal of Construction Engineering and Management, 142*(5), 6. Retrieved from <Go to ISI>://WOS:000374774800006. doi:10.1061/(asce)co.1943-7862.0001094

Love, P. E. D., Matthews, J., Simpson, I., Hill, A., & Olatunji, O. A. (2014). A benefits realization management building information modeling framework for asset owners. *Automation in Construction, 37*, 1-10. Retrieved from <Go to ISI>://WOS:000329562700001. doi:10.1016/j.autcon.2013.09.007

Love, P. E. D., Simpson, I., Hill, A., & Standing, C. (2013). From justification to evaluation: Building information modeling for asset owners. *Automation in Construction, 35,* 208-216. Retrieved from <Go to ISI>://WOS:000325742500017. doi:10.1016/j.autcon.2013.05.008

Lu, W. S., Peng, Y., Shen, Q. P., & Li, H. (2013). Generic model for measuring benefits of BIM as a learning tool in construction tasks. *Journal of Construction Engineering and Management-Asce, 139*(2), 195-203. Retrieved from <Go to ISI>://WOS:000316550900008. doi:10.1061/(asce)co.1943-7862.0000585

Lu, W. S., Webster, C., Chen, K., Zhang, X. L., & Chen, X. (2017). Computational Building Information Modelling for construction waste management: Moving from rhetoric to reality. *Renewable & Sustainable Energy Reviews, 68*, 587-595. Retrieved from <Go to ISI>://WOS:000391899200043. doi:10.1016/j.rser.2016.10.029

Lu, Y., Wu, Z., Chang, R., & Li, Y. (2017). Building Information Modeling (BIM) for green buildings: A critical review and future directions. *Automation in Construction, 83*, 134-148.

Lumpkin, G. T., & Dess, G. G. (2001). Linking two dimensions of entrepreneurial orientation to firm performance: The moderating role of environment and industry life cycle. *Journal of business venturing, 16*(5), 429-451.

Luo, H. B., & Gong, P. S. (2015). A BIM-based Code Compliance Checking Process of Deep Foundation Construction Plans. *Journal of Intelligent & Robotic Systems, 79*(3-4), 549-576. Retrieved from <Go to ISI>://WOS:000360311800016. doi:10.1007/s10846-014-0120-z

Madrid-Guijarro, A., Garcia, D., & Van Auken, H. (2009). Barriers to innovation among Spanish manufacturing SMEs. *Journal of small business management, 47*(4), 465-488.

Makadok, R., & Coff, R. (2002). The theory of value and the value of theory: Breaking new ground versus reinventing the wheel. In: JSTOR.

Mancini, M., Wang, X. Y., Skitmore, M., & Issa, R. (2017). Editorial for IJPM special issue on advances in building information modeling (BIM) for construction projects. *International Journal of Project Management*, *35*(4), 656-657. Retrieved from <Go to ISI>://WOS:000399862900009. doi:10.1016/j.ijproman.2016.12.008

Markides, C. C., & Williamson, P. J. (1996). Corporate diversification and organizational structure: A resource-based view. *Academy of Management journal*, *39*(2), 340-367.

Markman, G. D., Espina, M. I., & Phan, P. H. (2004). Patents as surrogates for inimitable and non-substitutable resources. *Journal of management*, *30*(4), 529-544.

Marsh, S. J., & Stock, G. N. (2006). Creating dynamic capability: The role of intertemporal integration, knowledge retention, and interpretation. *Journal of Product Innovation Management*, *23*(5), 422-436.

Martinez-Aires, M. D., Lopez-Alonso, M., & Martinez-Rojas, M. (2018). Building information modeling and safety management: A systematic review. *Safety Science*, *101*, 11-18. Retrieved from <Go to ISI>://WOS:000417009600002. doi:10.1016/j.ssci.2017.08.015

Martinsuo, M., Hensman, N., Artto, K., Kujala, J., & Jaafari, A. (2006). Project-based management as an organizational innovation: Drivers, changes, and benefits of adopting project-based management. *Project Management Journal*, *37*(3), 87-97.

Marzouk, M., Abdelkader, E. M., & Al-Gahtani, K. (2017). Building information modeling-based model for calculating direct and indirect emissions in construction projects. *Journal Of Cleaner Production*, *152*, 351-363. Retrieved from http://www.sciencedirect.com/science/article/pii/S0959652617305905. doi:https://doi.org/10.1016/j.jclepro.2017.03.138

Marzouk, M., Azab, S., & Metawie, M. (2018). BIM-based approach for optimizing life cycle costs of sustainable buildings. *Journal of cleaner production*, *188*, 217-226.

Marzouk, M., & Othman, A. (2017). Modeling the performance of sustainable sanitation systems using building information modeling. *Journal of cleaner production*, *141*, 1400-1410.

Mayer, N. Z., & Roberta, A. G. (2017). Social movement organizations: Growth, decay, and change. In *Social Movements in an organizational society* (pp. 121-142): Routledge.

McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological methods, 23*(3), 412.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology, 27*(1), 415-444.

McWilliams, A., Van Fleet, D. D., & Cory, K. D. (2002). Raising rivals' costs through political strategy: An extension of resource-based theory. *Journal of Management Studies, 39*(5), 707-724.

Meijer, A., & Bolívar, M. P. R. (2016). Governing the smart city: a review of the literature on smart urban governance. *international review of administrative sciences, 82*(2), 392-408.

Merschbrock, C., Hosseini, M. R., Martek, I., Arashpour, M., & Mignone, G. (2018). Collaborative role of sociotechnical components in BIM-based construction networks in two hospitals. *Journal of Management in Engineering, 34*(4), 05018006.

Michaelis, B., Rogbeer, S., Schweizer, L., & Özleblebici, Z. (2021). Clarifying the boundary conditions of value creation within dynamic capabilities framework: a grafting approach. *Review of Managerial Science, 15*(6), 1797-1820.

Miettinen, R., & Paavola, S. (2014). Beyond the BIM utopia: Approaches to the development and implementation of building information modeling. *Automation in Construction, 43*, 84-91. Retrieved from <Go to ISI>://WOS:000338814900010. doi:10.1016/j.autcon.2014.03.009

Mitropoulos, P., & Tatum, C. (1999). Technology adoption decisions in construction organizations. *Journal of Construction Engineering and Management, 125*(5), 330-338.

Mitropoulos, P., & Tatum, C. B. (2000). Forces driving adoption of new information technologies. *Journal of Construction Engineering and Management, 126*(5), 340-348.

Moran, P. (2005). Structural vs. relational embeddedness: Social capital and managerial performance. *Strategic management journal, 26*(12), 1129-1151.

Mousavi, S., Bossink, B., & van Vliet, M. (2018). Dynamic capabilities and organizational routines for managing innovation towards sustainability. *Journal of cleaner production, 203*, 224-239.

Muchungu, P. (2012). The contribution of human factors in the performance of construction projects in Kenya. *Unpublished Phd. Thesis. University of Nairobi*.

Mulgan, G., & Albury, D. (2003). Innovation in the public sector. *Strategy Unit, Cabinet Office, 1*(1), 40.

Müller, R., Geraldi, J., & Turner, J. R. (2011). Relationships between leadership and success in different types of project complexities. *IEEE Transactions on Engineering Management, 59*(1), 77-90.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of management review, 23*(2), 242-266.

Nam, C., & Tatum, C. (1988). Major characteristics of constructed products and resulting limitations of construction technology. *Construction management and economics, 6*(2), 133-147.

Nam, C. H., & Tatum, C. B. (1992). Strategies for technology push: Lessons from construction innovations. *Journal of Construction Engineering and Management, 118*(3), 507-524.

Naseer, S., Khawaja, K. F., Qazi, S., Syed, F., & Shamim, F. (2021). How and when information proactiveness leads to operational firm performance in the banking sector of Pakistan? The roles of open innovation, creative cognitive style, and climate for innovation. *International Journal of Information Management, 56*, 102260.

Naumovska, I., Gaba, V., & Greve, H. (2021). The diffusion of differences: A review and reorientation of 20 years of diffusion research. *Academy of Management Annals*(ja).

Nawari, N. O. (2012). BIM standard in off-site construction. *Journal of Architectural Engineering, 18*(2), 107-113.

Näyhä, A. (2020). Finnish forest-based companies in transition to the circular bioeconomy-drivers, organizational resources and innovations. *Forest Policy and Economics, 110*, 101936.

NBS. (2018). What is Building Information Modelling (BIM)? Retrieved from https://www.thenbs.com/knowledge/what-is-building-information-modelling-bim

Nelson, R. R., & Winter, S. G. (1982). The Schumpeterian tradeoff revisited. *The American Economic Review, 72*(1), 114-132.

Ngowtanasawan, G. (2017). Factor analysis of BIM adoption in the Thai architectural and engineering design industry. *Suranaree Journal of Science and Technology, 24*(4), 415-422. Retrieved from <Go to ISI>://WOS:000424420700004.

NIBS. (2018). National BIM Standard - United States® Version 3. Retrieved from http://www.nationalbimstandard.org/files/NBIMS-US_V3_3_Terms_and_Definitions.pdf

Oraee, M., Hosseini, M. R., Papadonikolaki, E., Palliyaguru, R., & Arashpour, M. (2017). Collaboration in BIM-based construction networks: A bibliometric-qualitative literature review. *International Journal of Project Management, 35*(7), 1288-1301.

Owen, R., Pansera, M., Macnaghten, P., & Randles, S. (2021). Organisational institutionalisation of responsible innovation. *Research Policy, 50*(1), 104132.

Ozaki, R. (2003). Customer-focused approaches to innovation in housebuilding. *Construction management and economics, 21*(6), 557-564.

Panteli, C., Kylili, A., & Fokaides, P. A. (2020). Building information modelling applications in smart buildings: From design to commissioning and beyond A critical review. *Journal of cleaner production, 265*, 121766.

Papadonikolaki, E., & Wamelink, H. (2017). Inter- and intra-organizational conditions for supply chain integration with BIM. *Building Research and Information, 45*(6), 649-664. Retrieved from <Go to ISI>://WOS:000405329900006. doi:10.1080/09613218.2017.1301718

Papadonikolaki, E., & Wamelink, H. (2017). Inter-and intra-organizational conditions for supply chain integration with BIM. *Building research & information, 45*(6), 649-664.

Park, H., Han, S. H., Rojas, E. M., Son, J., & Jung, W. (2011). Social network analysis of collaborative ventures for overseas construction projects. *Journal of Construction Engineering and Management, 137*(5), 344-355.

Park, J. H., & Lee, G. (2017). Design coordination strategies in a 2D and BIM mixed-project environment: social dynamics and productivity. *Building Research and Information, 45*(6), 631-648. Retrieved from <Go to ISI>://WOS:000405329900005. doi:10.1080/09613218.2017.1288998

Parn, E. A., Edwards, D. J., & Sing, M. C. P. (2017). The building information modelling trajectory in facilities management: A review. *Automation in Construction, 75*, 45-55. Retrieved from <Go to ISI>://WOS:000393007300005. doi:10.1016/j.autcon.2016.12.003

Peng, C. (2016). Calculation of a building's life cycle carbon emissions based on Ecotect and building information modeling. *Journal of cleaner production, 112*, 453-465.

Phaal, R., & Muller, G. (2009). An architectural framework for roadmapping: Towards visual strategy. *Technological forecasting and social change, 76*(1), 39-49.

Piazza, A., & Castellucci, F. (2014). Status in organization and management theory. *Journal of management, 40*(1), 287-315.

Piening, E. P., & Salge, T. O. (2015). Understanding the antecedents, contingencies, and performance implications of process innovation: A dynamic capabilities perspective. *Journal of Product Innovation Management, 32*(1), 80-97.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of management, 12*(4), 531-544.

Poirier, E. A., Staub-French, S., & Forgues, D. (2015). Measuring the impact of BIM on labor productivity in a small specialty contracting enterprise through action-research. *Automation in Construction, 58*, 74-84.

Poister, T. H. (2010). The future of strategic planning in the public sector: Linking strategic management and performance. *Public Administration Review, 70*, s246-s254.

Porwal, A., & Hewage, K. N. (2013). Building Information Modeling (BIM) partnering framework for public construction projects. *Automation in Construction, 31*, 204-214. Retrieved from <Go to ISI>://WOS:000315933100020. doi:10.1016/j.autcon.2012.12.004

Powell, W. W. (1987). Hybrid organizational arrangements: new form or transitional development? *California management review, 30*(1), 67-87.

Powell, W. W., & DiMaggio, P. J. (2012). *The new institutionalism in organizational analysis*: University of Chicago press.

Prasanna, R., Jayasundara, J., Naradda Gamage, S. K., Ekanayake, E., Rajapakshe, P., & Abeyrathne, G. (2019). Sustainability of smes in the competition: A systemic review on technological challenges and sme performance. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(4), 100.

Priem, R. L., & Butler, J. E. (2001). Is the resource-based “view” a useful perspective for strategic management research? *Academy of management review, 26*(1), 22-40.

Putnam, R. D. (1995). Tuning in, tuning out: The strange disappearance of social capital in America. *PS: Political science & politics, 28*(4), 664-683.

Qi, G., Shen, L. Y., Zeng, S., & Jorge, O. J. (2010). The drivers for contractors’ green innovation: an industry perspective. *Journal of cleaner production, 18*(14), 1358-1365.

Raouf, A. M. I., & Al-Ghamdi, S. G. (2019). Building information modelling and green buildings: challenges and opportunities. *Architectural Engineering and Design Management, 15*(1), 1-28. Retrieved from <Go to ISI>://WOS:000451587100001. doi:10.1080/17452007.2018.1502655

Reichstein, T., Salter, A. J., & Gann, D. M. (2005). Last among equals: a comparison of innovation in construction, services and manufacturing in the UK. *Construction management and economics, 23*(6), 631-644.

Ripley, R. M., Snijders, T. A., Boda, Z., Vörös, A., & Preciado, P. (2011). Manual for RSIENA. *University of Oxford, Department of Statistics, Nuffield College, 1*, 2011.

Sacks, R., Gurevich, U., & Shrestha, P. (2016). A review of building information modeling protocols, guides and standards for large construction clients. *Journal of Information Technology in Construction, 21*, 479-503. Retrieved from <Go to ISI>://WOS:000396453500011.

Saieg, P., Sotelino, E. D., Nascimento, D., & Caiado, R. G. G. (2018). Interactions of Building Information Modeling, Lean and Sustainability on the Architectural, Engineering and Construction industry: A systematic review. *Journal of Cleaner Production, 174*, 788-806. Retrieved from <Go to ISI>://WOS:000424727100072. doi:10.1016/j.jclepro.2017.11.030

Sanhudo, L., Ramos, N. M. M., Martins, J. P., Almeida, R., Barreira, E., Simoes, M. L., & Cardoso, V. (2018). Building information modeling for energy retrofitting - A review. *Renewable & Sustainable Energy Reviews, 89*, 249-260. Retrieved from <Go to ISI>://WOS:000430853300021. doi:10.1016/j.rser.2018.03.064

Scherer, F. M. (2015). First mover advantages and optimal patent protection. *The Journal of Technology Transfer, 40*(4), 559-580.

Schoemaker, P. J., Heaton, S., & Teece, D. (2018). Innovation, dynamic capabilities, and leadership. *California management review, 61*(1), 15-42.

Seaden, G., & Manseau, A. (2001). Public policy and construction innovation. *Building research & information, 29*(3), 182-196.

Shelton, R. C., Lee, M., Brotzman, L. E., Crookes, D. M., Jandorf, L., Erwin, D., & Gage-Bouchard, E. A. (2019). Use of social network analysis in the development, dissemination, implementation, and sustainability of health behavior interventions for adults: A systematic review. *Social science & medicine, 220*, 81-101.

Siagian, H., Jade, K., & Tarigan, Z. (2020). The role of affective leadership in improving firm performance through the integrated internal system and external integration FMCG Industry. *International Journal of Data and Network Science, 4*(4), 365-372.

Simonin, B. L. (2004). An empirical investigation of the process of knowledge transfer in international strategic alliances. *Journal of international business studies, 35*(5), 407-427.

Singh, M. M., Sawhney, A., & Borrmann, A. (2019). Integrating rules of modular coordination to improve model authoring in BIM. *International Journal of Construction Management, 19*(1), 15-31.

Slater, S. F., & Narver, J. C. (1993). Product-market strategy and performance: an analysis of the Miles and Snow strategy types. *European journal of marketing, 27*(10), 33-51.

Slaughter, E. S. (1993). Builders as sources of construction innovation. *Journal of Construction Engineering and Management, 119*(3), 532-549.

Slaughter, E. S. (1998). Models of construction innovation. *Journal of Construction Engineering and Management, 124*(3), 226-231.

Snijders, T. A. (2001). The statistical evaluation of social network dynamics. *Sociological methodology, 31*(1), 361-395.

Snijders, T. A., Van de Bunt, G. G., & Steglich, C. E. (2010). Introduction to stochastic actor-based models for network dynamics. *Social networks, 32*(1), 44-60.

Snowden, D. J., & Boone, M. E. (2007). A leader's framework for decision making. *Harvard business review, 85*(11), 68.

Soust-Verdaguer, B., Llatas, C., & Garcia-Martinez, A. (2017). Critical review of bim-based LCA method to buildings. *Energy and Buildings, 136*, 110-120. Retrieved from <Go to ISI>://WOS:000392354100010. doi:10.1016/j.enbuild.2016.12.009

Spender, J.-C. (1994). Organizational knowledge, collective practice and Penrose rents. *International business review, 3*(4), 353-367.

Spender, J.-C. (2014). *Business strategy: Managing uncertainty, opportunity, and enterprise*: Oxford University Press.

Staykova, K. S., & Damsgaard, J. (2015). The race to dominate the mobile payments platform: Entry and expansion strategies. *Electronic Commerce Research and Applications, 14*(5), 319-330.

Stewart, R. A., Mohamed, S., & Daet, R. (2002). Strategic implementation of IT/IS projects in construction: a case study. *Automation in Construction, 11*(6), 681-694.

Strandholm, K., Kumar, K., & Subramanian, R. (2004). Examining the interrelationships among perceived environmental change, strategic response, managerial characteristics, and organizational performance. *Journal of Business Research, 57*(1), 58-68.

Succar, B. (2009). Building information modelling framework: A research and delivery foundation for industry stakeholders. *Automation in Construction, 18*(3), 357-375. Retrieved from <Go to ISI>://WOS:000264211200014. doi:10.1016/j.autcon.2008.10.003

Sun, C. S., Jiang, S. H., Skibniewski, M. J., Man, Q. P., & Shen, L. Y. (2017). A literature review of the factors limiting the application of BIM in the construction industry. *Technological and Economic Development of Economy, 23*(5), 764-779. Retrieved from <Go to ISI>://WOS:000403778000005. doi:10.3846/20294913.2015.1087071

Taherdoost, H. (2016). Validity and reliability of the research instrument; how to test the validation of a questionnaire/survey in a research. *How to test the validation of a questionnaire/survey in a research (August 10, 2016)*.

Tam, V. W., & Tam, C. M. (2008). Waste reduction through incentives: a case study. *Building research & information, 36*(1), 37-43.

Tan, T., Chen, K., Xue, F., & Lu, W. J. J. o. C. P. (2019). Barriers to Building Information Modeling (BIM) implementation in China's prefabricated construction: An interpretive structural modeling (ISM) approach. *219*, 949-959.

Tan, Y., Fang, Y., Zhou, T., Gan, V. J. L., & Cheng, J. C. P. (2019). BIM-supported 4D acoustics simulation approach to mitigating noise impact on maintenance workers on offshore oil and gas platforms. *Automation in Construction, 100*, 1-10. Retrieved from http://www.sciencedirect.com/science/article/pii/S0926580518306708. doi:https://doi.org/10.1016/j.autcon.2018.12.019

Tan, Y., Song, Y., Liu, X., Wang, X., & Cheng, J. C. P. (2017). A BIM-based framework for lift planning in topsides disassembly of offshore oil and gas platforms. *Automation in Construction, 79*, 19-30. Retrieved from http://www.sciencedirect.com/science/article/pii/S0926580516303910. doi:https://doi.org/10.1016/j.autcon.2017.02.008

Tang, Y., Wang, G., Li, H., & Cao, D. (2018). Dynamics of collaborative networks between contractors and subcontractors in the construction industry: Evidence from national quality award projects in China. *Journal of Construction Engineering and Management, 144*(9), 05018009.

Tang, Y., Wang, G., Li, H., Cao, D., & Li, X. (2019). Comparing project-based collaborative networks for BIM implementation in public and private sectors: a longitudinal study in Hong Kong. *Advances in Civil Engineering, 2019*.

Tatum, C. (1989). Organizing to increase innovation in construction firms. *Journal of Construction Engineering and Management, 115*(4), 602-617.

Tatum, C., & Funke, A. (1988). Partially automated grading: Construction process innovation. *Journal of Construction Engineering and Management, 114*(1), 19-35.

Tatum, C. B. (1987). Process of innovation in construction firm. *Journal of Construction Engineering and Management, 113*(4), 648-663.

Taylor, J. B. (2007). *Housing and monetary policy*. Retrieved from

Taylor, J. E. (2007). Antecedents of successful three-dimensional computer-aided design implementation in design and construction networks. *Journal of Construction Engineering and Management, 133*(12), 993-1002.

Taylor, J. E., Levitt, R., & Villarroel, J. A. (2009). Simulating learning dynamics in project networks. *Journal of Construction Engineering and Management, 135*(10), 1009-1015.

Teece, D., & Pisano, G. (2003). The dynamic capabilities of firms. In *Handbook on knowledge management* (pp. 195-213): Springer.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal, 18*(7), 509-533.

Teng, Y., Li, X., Wu, P., & Wang, X. (2019). Using cooperative game theory to determine profit distribution in IPD projects. *International Journal of Construction Management, 19*(1), 32-45. Retrieved from https://doi.org/10.1080/15623599.2017.1358075. doi:10.1080/15623599.2017.1358075

Terziovski, M. (2010). Innovation practice and its performance implications in small and medium enterprises (SMEs) in the manufacturing sector: a resource-based view. *Strategic management journal, 31*(8), 892-902.

Tortorella, G. L., Vergara, A. M. C., Garza-Reyes, J. A., & Sawhney, R. (2020). Organizational learning paths based upon industry 4.0 adoption: An empirical study with Brazilian manufacturers. *International Journal of Production Economics, 219*, 284-294.

Tsai, W. (2000). Social capital, strategic relatedness and the formation of intraorganizational linkages. *Strategic management journal, 21*(9), 925-939.

Tsai, W., & Ghoshal, S. (1998). Social capital and value creation: The role of intrafirm networks. *Academy of Management journal, 41*(4), 464-476.

van Nederveen, G. A., & Tolman, F. P. (1992). Modelling multiple views on buildings. *Automation in Construction, 1*(3), 215-224.

Vargo, S. L., Akaka, M. A., & Wieland, H. (2020). Rethinking the process of diffusion in innovation: A service-ecosystems and institutional perspective. *Journal of Business Research, 116*, 526-534.

Venugopal, M., Eastman, C. M., Sacks, R., & Teizer, J. (2012). Semantics of model views for information exchanges using the industry foundation class schema.

Advanced Engineering Informatics, 26(2), 411-428. Retrieved from <Go to ISI>://WOS:000308122400019. doi:10.1016/j.aei.2012.01.005

Venugopal, M., Eastman, C. M., & Teizer, J. (2015). An ontology-based analysis of the industry foundation class schema for building information model exchanges. *Advanced Engineering Informatics, 29*(4), 940-957. Retrieved from <Go to ISI>://WOS:000366769500018. doi:10.1016/j.aei.2015.09.006

Verona, G., & Ravasi, D. (2003). Unbundling dynamic capabilities: an exploratory study of continuous product innovation. *Industrial and corporate change, 12*(3), 577-606.

Wang, J., Wang, X. Y., Shou, W. C., Chong, H. Y., & Guo, J. (2016). Building information modeling-based integration of MEP layout designs and constructability. *Automation in Construction, 61*, 134-146. Retrieved from <Go to ISI>://WOS:000366779700012. doi:10.1016/j.autcon.2015.10.003

Wang, J. Y., Wu, H. Y., Duan, H. B., Zillante, G., Zuo, J., & Yuan, H. P. (2018). Combining life cycle assessment and Building Information Modelling to account for carbon emission of building demolition waste: A case study. *Journal of Cleaner Production, 172*, 3154-3166. Retrieved from <Go to ISI>://WOS:000423002500014. doi:10.1016/j.jclepro.2017.11.087

Wang, K. C., Wang, W. C., Wang, H. H., Hsu, P. Y., Wu, W. H., & Kung, C. J. (2016). Applying building information modeling to integrate schedule and cost for establishing construction progress curves. *Automation in Construction, 72*, 397-410. Retrieved from <Go to ISI>://WOS:000390722200015. doi:10.1016/j.autcon.2016.10.005

Wang, X. Y., Love, P. E. D., Kim, M. J., Park, C. S., Sing, C. P., & Hou, L. (2013). A conceptual framework for integrating building information modeling with augmented reality. *Automation in Construction, 34*, 37-44. Retrieved from <Go to ISI>://WOS:000321092700005. doi:10.1016/j.autcon.2012.10.012

Wang, Y., Li, H., & Wu, Z. (2019). Attitude of the Chinese public toward off-site construction: A text mining study. *Journal of cleaner production, 238*, 117926.

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’networks. *nature, 393*(6684), 440-442.

Wayne, S. J., Shore, L. M., & Liden, R. C. (1997). Perceived organizational support and leader-member exchange: A social exchange perspective. *Academy of Management journal, 40*(1), 82-111.

Wells, H. (2012). How effective are project management methodologies? An explorative evaluation of their benefits in practice. *Project Management Journal, 43*(6), 43-58.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal, 5*(2), 171-180.

West, J. (2014). Collaborative patterns and power imbalance in strategic alliance networks. *Journal of Construction Engineering and Management, 140*(6), 04014010.

West, J., & Gallagher, S. (2006). Challenges of open innovation: the paradox of firm investment in open-source software. *R&d Management, 36*(3), 319-331.

West, M. A., & Anderson, N. R. (1996). Innovation in top management teams. *Journal of Applied psychology, 81*(6), 680.

White, H. C. (1981). Where do markets come from? *American journal of sociology, 87*(3), 517-547.

White, H. C. (2012). *Identity and control*: Princeton University Press.

Whyte, J. (2003). Innovation and users: virtual reality in the construction sector. *Construction management and economics, 21*(6), 565-572.

Wijethilake, C. (2017). Proactive sustainability strategy and corporate sustainability performance: The mediating effect of sustainability control systems. *Journal of environmental management, 196*, 569-582.

Williams, B., Onsman, A., & Brown, T. (2010). Exploratory factor analysis: A five-step guide for novices. *Australasian journal of paramedicine, 8*(3).

Wong, A. K., Wong, F. K., & Nadeem, A. (2011). Government roles in implementing building information modelling systems: Comparison between Hong Kong and the United States. *Construction Innovation*.

Wong, K. d., & Fan, Q. (2013). Building information modelling (BIM) for sustainable building design. *Facilities*.

Wu, Z., Chen, C., Cai, Y., Lu, C., Wang, H., & Yu, T. (2019). BIM-Based Visualization Research in the Construction Industry: A Network Analysis. *International Journal of Environmental Research and Public Health, 16*(18),

3473. Retrieved from https://www.mdpi.com/1660-4601/16/18/3473. doi:10.3390/ijerph16183473

Wunker, S. (2012). Better growth decisions: early mover, fast follower or late follower? *Strategy & Leadership*.

Xie, C., Wu, D., Luo, J., & Hu, X. (2010). A case study of multi-team communications in construction design under supply chain partnering. *Supply Chain Management: An International Journal*.

Xu, H., Feng, J., & Li, S. (2014). Users-orientated evaluation of building information model in the Chinese construction industry. *Automation in Construction, 39*, 32-46. Retrieved from http://www.sciencedirect.com/science/article/pii/S0926580513002161. doi:https://doi.org/10.1016/j.autcon.2013.12.004

Xu, X., Lan, L., Shen, J., Sun, Y., & Lian, Z. (2021). Five hypotheses concerned with bedroom environment and sleep quality: A questionnaire survey in Shanghai city, China. *Building and Environment, 205*, 108252.

Xue, X., Zhang, R., Yang, R., & Dai, J. (2014). Innovation in construction: a critical review and future research. *International Journal of Innovation Science*.

Yang, X., Hu, M., Wu, J., & Zhao, B. (2018). Building-information-modeling enabled life cycle assessment, a case study on carbon footprint accounting for a residential building in China. *Journal of cleaner production, 183*, 729-743.

Yitmen, I. (2007). The challenge of change for innovation in construction: A North Cyprus perspective. *Building and Environment, 42*(3), 1319-1328.

Yu, T., Man, Q., Wang, Y., Shen, G. Q., Hong, J., Zhang, J., & Zhong, J. (2019). Evaluating different stakeholder impacts on the occurrence of quality defects in offsite construction projects: A Bayesian-network-based model. *Journal of Cleaner Production, 241*, 118390. Retrieved from http://www.sciencedirect.com/science/article/pii/S0959652619332603. doi:https://doi.org/10.1016/j.jclepro.2019.118390

Zaheer, A., Gözübüyük, R., & Milanov, H. (2010). It's the connections: The network perspective in interorganizational research. *Academy of Management Perspectives, 24*(1), 62-77.

Zahra, S. A., & Nielsen, A. P. (2002). Sources of capabilities, integration and technology commercialization. *Strategic management journal, 23*(5), 377-398.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities: A review, model and research agenda. *Journal of Management Studies, 43*(4), 917-955.

Zane, L. J. (2011). How social capital and firm knowledge influence the acquisition of resources in technology based new ventures.

Zelizer, V. A. (2000). The purchase of intimacy. *Law & Social Inquiry, 25*(3), 817-848.

Zhang, X., Azhar, S., Nadeem, A., & Khalfan, M. (2018). Using Building Information Modelling to achieve Lean principles by improving efficiency of work teams. *International Journal of Construction Management, 18*(4), 293-300. Retrieved from <Go to ISI>://WOS:000430212300003. doi:10.1080/15623599.2017.1382083

Zhao, X. B., Feng, Y. B., Pienaar, J., & O'Brien, D. (2017). Modelling paths of risks associated with BIM implementation in architectural, engineering and construction projects. *Architectural Science Review, 60*(6), 472-482. Retrieved from <Go to ISI>://WOS:000416690100005. doi:10.1080/00038628.2017.1373628

Zhao, X. B., Wu, P., & Wang, X. Y. (2018). Risk paths in BIM adoption: empirical study of China. *Engineering Construction and Architectural Management, 25*(9), 1170-1187. Retrieved from <Go to ISI>://WOS:000445061100004. doi:10.1108/ecam-08-2017-0169

Zhou, Y., Ding, L. Y., Rao, Y., Luo, H. B., Medjdoub, B., & Zhong, H. (2017). Formulating project-level building information modeling evaluation framework from the perspectives of organizations: A review. *Automation in Construction, 81*, 44-55. Retrieved from <Go to ISI>://WOS:000405536700006. doi:10.1016/j.autcon.2017.05.004

Zhou, Y., Hong, J., Zhu, K., Yang, Y., & Zhao, D. (2018). Dynamic capability matters: Uncovering its fundamental role in decision making of environmental innovation. *Journal of cleaner production, 177,* 516-526.

Zietsma, C., Groenewegen, P., Logue, D. M., & Hinings, C. R. (2017). Field or fields? Building the scaffolding for cumulation of research on institutional fields. *Academy of Management Annals, 11*(1), 391-450.

Zou, Y., Kiviniemi, A., & Jones, S. W. (2017). A review of risk management through BIM and BIM-related technologies. *Safety Science, 97*, 88-98.

Retrieved from <Go to ISI>://WOS:000404304400012. doi:10.1016/j.ssci.2015.12.027

Appendices

Appendix A. Face-to-face Interview Questions: Part I

THE HONG KONG
POLYTECHNIC UNIVERSITY
香港理工大學

Survey on Diffusion of BIM Implementation Practices in Collaborative Networks in Hong Kong

Dear Sir or Madam,

As a milestone technology to parametrically model and integratively manage project lifecycle information, building information modeling (BIM) has drawn increasing interest from construction practitioners over the past decade. However, the diffusion of the technology among industry practitioners at present is still not widespread in Hong Kong. Financially supported by the Public Policy Research Funding Scheme from the Hong Kong government (Grant No. 2016.A6.075.17A), this investigation aims to empirically assess the firm-level diffusion of BIM implementation in construction projects in Hong Kong from a network perspective. Given your expertise and experience related to BIM, you are cordially invited to spare your precious time to participate in our questionnaire survey.

Please answer the questions based on the information of your company/organization and you are encouraged to give some examples to illustrate the BIM practices of your company/organization. **All the answers should be based on the situations in Hong Kong**. It will take you about 10~20 minutes to complete the questionnaire, **please respond directly to the documents you receive and adjust the space according to your requirements**. All of the collected data will be used only for academic purposes, and the information related to specific projects and respondents will be kept in strict confidence. If you are interested in the research results, we will send you an electronic copy of the research report upon the accomplishment of this research. We greatly appreciate your support for our research!

Yours sincerely,
The Hong Kong Polytechnic University

Part I :Basic Information about Respondent

1. Company Name:

2. Position of respondent:

3. Is there independent BIM department/team in Hong Kong?

- *Size?*
- *Their main job?*
- *Hire BIM consultant? what’s their work scope?*

4. When BIM was firstly used in Hong Kong? In which project?

5. Percentage of BIM projects now in Hong Kong?

Part II: BIM Implementation Practices

6. The motivations and intentions to adopt BIM for your company? What's the difference between the past and the present?

7. Do you think your firm-level BIM adoption/implementation are influenced by any of the following bodies?

- *The government department*
- *The partners you have ever worked together (if there is, please list name of the company:____)*
- *The competitors in the market (if there is, please list name of the company:____)*
- *The industry associations (e.g. HKIBIM, CIC)*
- *The software developer (e.g. Autodesk)*
- *The academic university and research institute*

8. How BIM is used in your projects in general?

- *How the BIM models are generated and used?*
- *What are the most widely adopted BIM functions in your BIM-involved projects?*
- *What do you think about your adoption level in the BIM implementation areas related to construction activities?*
- *Are there any projects with full-life use of BIM (BIM is used in all project stages)? How many of them?*
- *Are there any trials or studies on the innovative application of BIM combined with new technologies? What are they?*

Part III: BIM Plans and Strategies

9. Is there standard, guide or library for BIM use in your company? Any special items in these documents?

10. Is there firm-level strategic plan for BIM implementation in your company?

11. If there is a strategic plan, any goals for each stage (e.g., rate of BIM-involved projects, rate of BIM-capable staff)? Where are you now?

End of the questionnaire. Thanks a lot for your support for our research!

Appendix B. Face-to-face Interview Questions Part: II

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Survey on Diffusion of BIM Implementation Practices in Collaborative Networks in Hong Kong

Dear Sir or Madam,

As a milestone technology to parametrically model and integratively manage project lifecycle information, building information modeling (BIM) has drawn increasing interest from construction practitioners over the past decade. However, the diffusion of the technology among industry practitioners at present is still not widespread in Hong Kong. Financially supported by the Public Policy Research Funding Scheme from the Hong Kong government (Grant No. 2016.A6.075.17A), this investigation aims to empirically assess the firm-level diffusion of BIM implementation in construction projects in Hong Kong from a network perspective. Given your expertise and experience related to BIM, you are cordially invited to spare your precious time to participate in our questionnaire survey. **Please answer the questions based on the information of your company/organization and you are encouraged to give some examples to illustrate the BIM practices of your company/organization**. **All the answers should be based on the situations in Hong Kong**. It will take you about 10~20 minutes to complete the questionnaire, **please respond directly to the documents you receive and adjust the space according to your requirements**.

All of the collected data will be used only for academic purposes, and the information related to specific projects and respondents will be kept in strict confidence. If you are interested in the research results, we will send you an electronic copy of the research report upon the accomplishment of this research. We greatly appreciate your support for our research!

Yours sincerely,
The Hong Kong Polytechnic University

Part I: *Basic Information about* Organizational Characteristics

1. Organizational type of your company/organization: (   )

A. Main contractor   B. Designer   C. Client

2. Approximate number of full-time employees in your company/organization: (   )

A. Below 50   B. 50–100   C. 1000-10000   D. Above 10000

3. Organizational type of your company/organization: (   )

A. Multi-national company   B. Local company/organization in Hong Kong

4. The year around which BIM was firstly used in your company/organization:

5. Approximate percentage of projects in your company/organization using BIM: (   )

A. Below 10% B. 10–20%   C. 21–30%   D. 31–40%   E. 41–50%   F. Above 50%

Part II: Organizational Capability Relating to BIM Implementation

Please indicate the extent to which you agree with the listed statements regarding ***the BIM implementation practice in your organization***

A	B	C	D	E	F	G
Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree

	【You could use “√” to mark your response.】	Disagree			>			Agree
		A	B	C	D	E	F	G
Organizational Integrating capability								
01	We have integrated and drawn on relevant/previous experience to advocate the use of BIM							
02	We have integrated and elaborated the existing technology and related personnel experience to advocate the use of BIM							
Organizational Learning Capability								
01	We have participated in frequent external BIM knowledge learning/training programs organized by the government /industry							
02	We have held frequent internal cross-department BIM knowledge sharing/learning program							
03	When collaborating with external organizations, we can proactively use BIM							
04	When collaborating with external organizations, we are willing to learn from collaborators							
Organizational Reconfiguring capability								
01	We can reconfigure and respond to meet changing government policy and industry-standard rapidly							

02	We can reconfigure and respond to changing market needs and trends rapidly							
03	We can reconfigure and respond to the competitors’ actions rapidly							
04	We can conduct effective communication and cooperation with cooperators when handling with the reconfiguring issues							

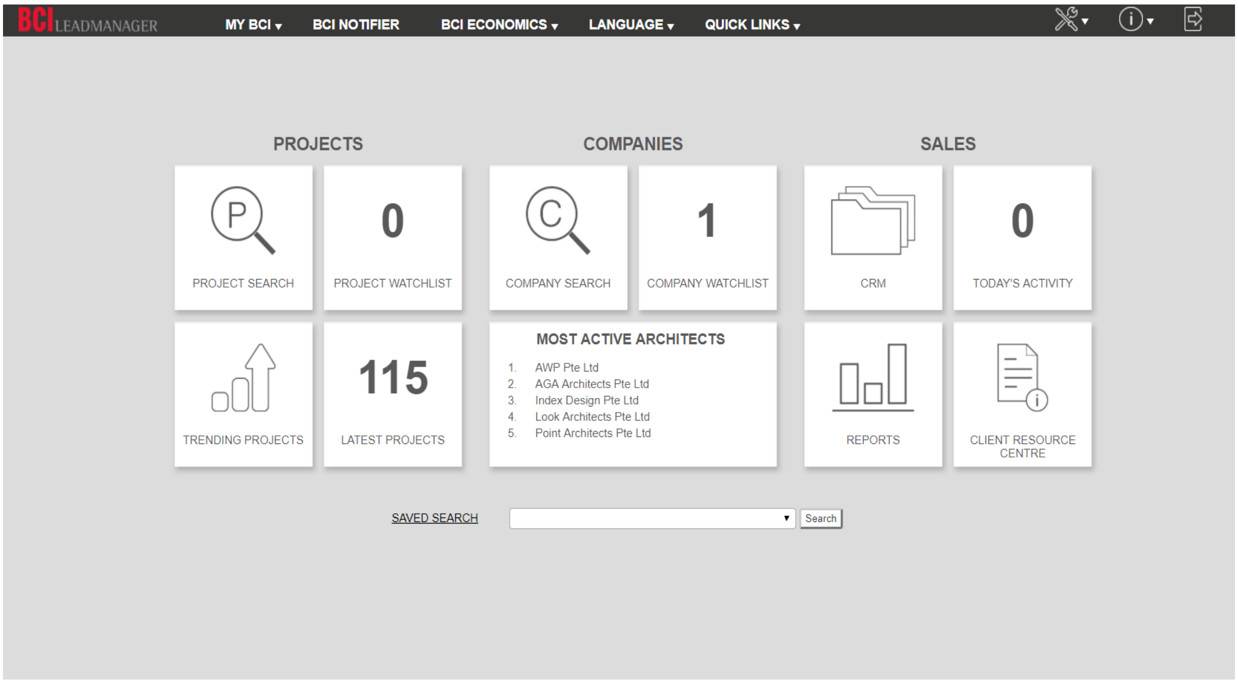
Part III: *Organizational Response Strategy Relating to BIM Implementation*

*Please indicate the extent to which you agree with the listed statements regarding **the response activities to the BIM implementation in your organization***

【You could use “√” to mark your response.】		Disagree			>	Agree		
		A	B	C	D	E	F	G
Pioneer/Leading Innovation Strategy								
01	We are willing to set up/upgrade the BIM department to maintain a good level of application of BIM							
02	We are willing to draw up a firm-level strategic plan (e.g., three or five years formal plan) for BIM implementation							
03	We are willing to actively respond to policy requirements or standard changes related to BIM implementation							
Follower/Opportunity Seeking Strategy								
01	We are willing to train staff/purchase hardware to meet the requirement from the government or partners							
02	We are willing to develop a standard/guide for BIM implementation to meet the requirement from the government or partner							
03	We are willing to work closely with partners to advance the level of BIM adoption (e.g., rate of BIM-involved projects; rate of BIM-capable staff)							
Wait-and-See Strategy								
01	We prefer to follow guidelines or partners’ requirements to adopt BIM in current projects							
02	We prefer to consider developing BIM-related goals in future projects							
Resistance/ Avoidance Strategy								
01	We faced some resistance in adopting/promoting the application of BIM							
02	We would not actively seek BIM cooperation projects							

End of the questionnaire. Thanks a lot for your support for our research!

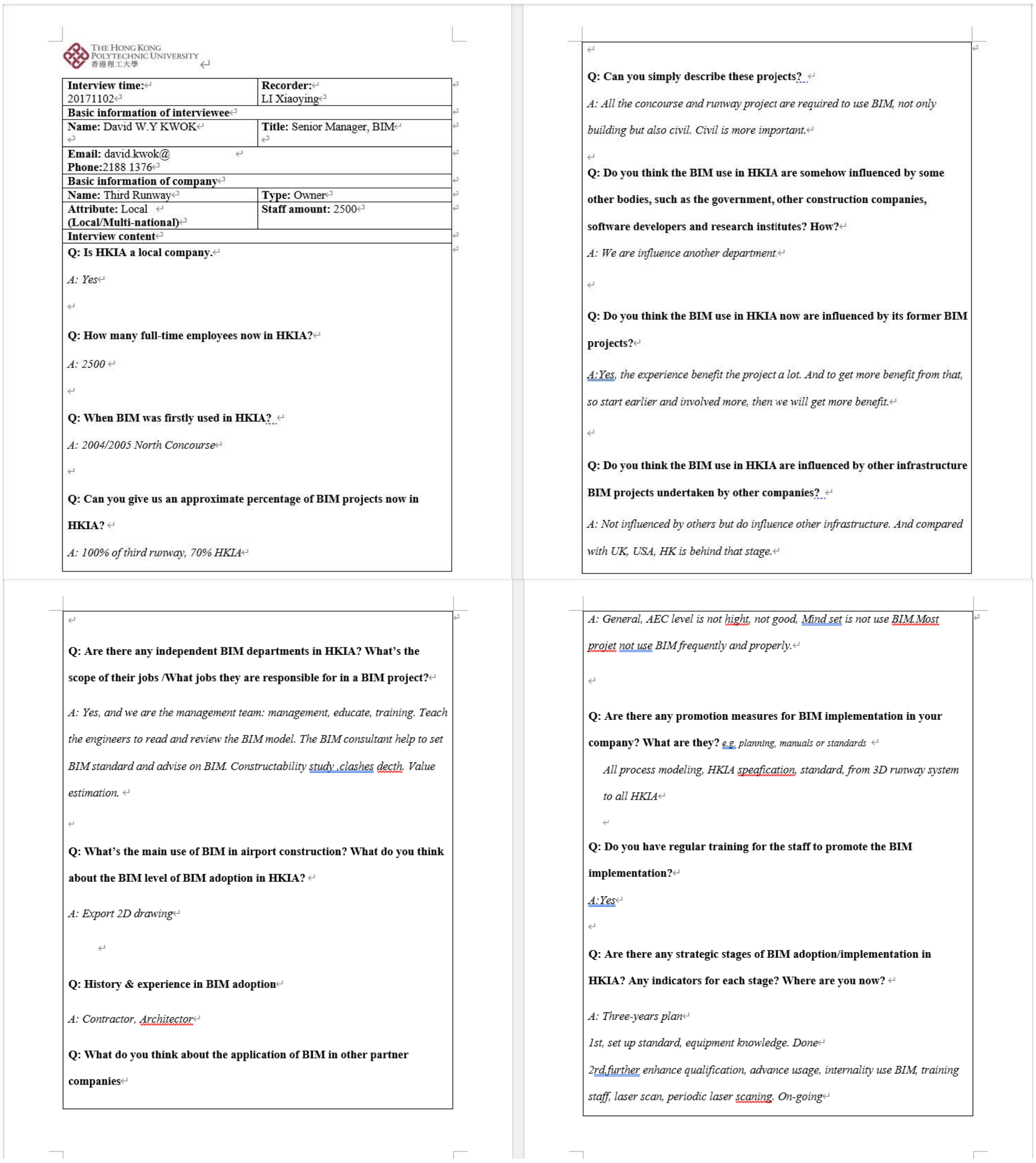
Appendix C. Snapshots of the Online Database



MOST ACTIVE ARCHITECTS

1. AWP Pte Ltd
2. AGA Architects Pte Ltd
3. Index Design Pte Ltd
4. Look Architects Pte Ltd
5. Point Architects Pte Ltd

Appendix D. Selected Sample of Interview Transcription



THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Interview time: 20171102	**Recorder:** LI Xiaoying
Basic information of interviewee	
Name: David W.Y KWOK	**Title:** Senior Manager, BIM
Email: david.kwok@ **Phone:**2188 1376	
Basic information of company	
Name: Third Runway	**Type:** Owner
Attribute: Local **(Local/Multi-national)**	**Staff amount:** 2500
Interview content	

Q: Is HKIA a local company.

A: Yes

Q: How many full-time employees now in HKIA?

A: 2500

Q: When BIM was firstly used in HKIA?

A: 2004/2005 North Concourse

Q: Can you give us an approximate percentage of BIM projects now in HKIA?

A: 100% of third runway, 70% HKIA

Q: Can you simply describe these projects?

A: All the concourse and runway project are required to use BIM, not only building but also civil. Civil is more important.

Q: Do you think the BIM use in HKIA are somehow influenced by some other bodies, such as the government, other construction companies, software developers and research institutes? How?

A: We are influence another department.

Q: Do you think the BIM use in HKIA now are influenced by its former BIM projects?

A:Yes, the experience benefit the project a lot. And to get more benefit from that, so start earlier and involved more, then we will get more benefit.

Q: Do you think the BIM use in HKIA are influenced by other infrastructure BIM projects undertaken by other companies?

A: Not influenced by others but do influence other infrastructure. And compared with UK, USA, HK is behind that stage.

Q: Are there any independent BIM departments in HKIA? What's the scope of their jobs /What jobs they are responsible for in a BIM project?

A: Yes, and we are the management team: management, educate, training. Teach the engineers to read and review the BIM model. The BIM consultant help to set BIM standard and advise on BIM. Constructability study ,clashes decth. Value estimation.

Q: What's the main use of BIM in airport construction? What do you think about the BIM level of BIM adoption in HKIA?

A: Export 2D drawing

Q: History & experience in BIM adoption

A: Contractor, Architector

Q: What do you think about the application of BIM in other partner companies

A: General, AEC level is not hight, not good, Mind set is not use BIM.Most projet not use BIM frequently and properly.

Q: Are there any promotion measures for BIM implementation in your company? What are they? *e.g. planning, manuals or standards*

All process modeling, HKIA speafication, standard, from 3D runway system to all HKIA

Q: Do you have regular training for the staff to promote the BIM implementation?

A:Yes

Q: Are there any strategic stages of BIM adoption/implementation in HKIA? Any indicators for each stage? Where are you now?

A: Three-years plan
1st, set up standard, equipment knowledge. Done
2rd,further enhance qualification, advance usage, internality use BIM, training staff, laser scan, periodic laser scaning. On-going