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How to use lean thinking to improve knowledge management performance of manufacturing supply chains

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Copyright Statement

HOW TO USE LEAN THINKING TO IMPROVE KNOWLEDGE MANAGEMENT PERFORMANCE OF MANUFACTURING SUPPLY CHAINS

by

JIANG PAN

A thesis submitted to the University of Plymouth

in partial fulfilment for the degree of

DOCTOR OF PHILOSOPHY

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Dedication

To my father: 潘青辉 and my mother: 江鲁荔

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I wish to extend the expression of my appreciation to cover my parents, grandmothers, uncle and cousin brother for their endless support and encouragement.

Author’s Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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2. Liu, S., Smith, M.H., Tuck, S., **Pan, J.,** Alkhuraiji, A., & Jayawickrama, U., (2015*), Where can knowledge-based decision support systems go in contemporary business management—a new architecture for the future*, Journal of Economics, Business and Management, 3 (5), pp.498-504.

Conference Paper:

1. **Pan, J.,** Liu, S., Tuck, S., & Alkhuraiji, A., (2013), *Optimising inventory level of global critical knowledge for integrated decision support*, The 26th EURO and INFORMS Joint International Conference, 1-4 July 2013, Rome, Italy.
2. Alkhuraiji, A., Liu, S., Annansingh, F., & Pan, J., (2013), Knowledge network modelling to support decision making for strategic intervention in IT project-oriented change management. The 26th EURO and INFORMS Joint International Conference, 1-4 July 2013, Rome, Italy.
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Abstract

This thesis aims to eliminate inefficient knowledge management activities and use Lean Principles as guidance to improve knowledge management performance in manufacturing supply chains. In order to achieve this aim, this research examines the causal relationships between *Knowledge Management Processes* (KMPs), 4 *Lean-KM Wastes* and 2 *Lean-KM Principles* in different countries, industries and company sizes.

This thesis employs a quantitative method. A theoretical model is built on rigorous literature reviews of supply chain knowledge management and Lean thinking studies, in-depth discussions, item review and pilot study with experts to signify ambiguity or misunderstanding with the items and to suggest modifications. The proposed model is empirically tested with survey data using 359 responses from two types of manufacturing industries (i.e. machinery and electronics manufacturing and food and drink industry), two types of business sizes (i.e. SMEs and Large companies), and two countries (i.e. China and the US).

The key output is a framework for Lean-Knowledge Management Processes (Lean-KMPs). With regard to the findings of the empirical research, three main constructs were successfully validated as multi-dimensional constructs. The results from path model analysis shows that most of the sub-hypotheses are supported. Only three of them were rejected in both aggregated-level path model analysis and multi-group analysis. The results have proven the four Lean-KM Wastes and two Lean-KM Principles having negative and positive effects on KMPs, respectively. The detailed findings of this thesis include five parts. Firstly, with respect to *Knowledge Acquisition* (KA), badly designed information systems are the biggest obstacles for improving the performance of KA. *Identification and Usage of Valuable Information and Knowledge* (IUVI) and *Encouraging Information and Knowledge Flow* (EIKF) are two factors that can enhance KA. In addition, big companies should build trustful relationships and improve the accessibility of required information with their supply chain. Secondly, concerning the performance of *Knowledge Selection* (KS), companies should only retain the most valuable information for avoiding overloaded databases, and information provider need to understand receiver's requirement and provide the most relevant information, so that could help receivers to store that information more effectively and also make the retrieval of it much easier. Thirdly, for enhancing the performance of *Knowledge Generation* (KG), companies should gather business information as comprehensive as possible. In addition, *Low Quality Information* (LQI) and *Insufficient Knowledge Inventory* (IKI) are two negative factors which could diminish the performance of KG. Moreover, the results also reveal that small or less resourceful companies should focus more on improving the information quality over quantity. Furthermore, well-developed IT systems, IUVI, and EIKF are important positive factors for large and/or machinery and electronics manufacturing's KG performance. Fourthly, as for *Knowledge Internalisation*

(KI), IUVI and EIKF are two positive factors to the performance of KI. While *Inappropriate Information System* (IIS) is the biggest obstacle of KI. Lastly, regarding to *Knowledge Externalisation* (KE), the results indicate that LQI and IKI are two negative factors to KE and IUVI is the only positive factor to KE.

This thesis synthesises Lean thinking, supply chain integration, and knowledge management to develop a comprehensive approach to improve the knowledge management performance of manufacturing supply chains. It has four theoretical contributions: 1) developed Lean-KMPs model and 19 hypotheses to improve the KM performance of manufacturing supply chains; 2) developed 4 Lean-KM wastes and 2 Lean-KM Principles based on the Lean thinking for manufacturing supply chain KM; 3) identified and developed 5 latent constructs for KMPs and 30 corresponding indicators to accurately measure companies' KM performance; 4) conducted industry-specific empirical studies, collected 359 useful data from different countries, different industries and different sized companies, and conducted three pairs of multi-group analyses based on these different contexts.

Various manufacturing companies in both heavy and light industries would benefit from applying the results of this study to improve their KM performance. The results also suggest that manufacturing practitioners should use a comprehensive approach to improve knowledge management processes in order to make sure that critical information and knowledge flow seamlessly and efficiently among their supply chain members, further to achieve successful supply chain integration.

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List of Abbreviations

ACCES	Accessibility
BPR	Business Process Re-Engineering
CM	Cultural Misfits
ECC	Expanding Communication Channel
EIKF	Encouraging Information and Knowledge Flow
ERP	Enterprise Resource Planning
IIS	Inappropriate Information System
IKI	Insufficient Knowledge Inventory
ILIO	Internal Legacy Information Overload
INCOMPA	Incompatibility
INFLEX	Inflexibility
IO	Information Overload
IT	Information Technology
IUVI	Identification & Usage of Valuable Information & Knowledge
KA	Knowledge Acquisition
KC	Knowledge Chain
KE	Knowledge Externalisation

KG	Knowledge Generation
KI	Knowledge Internalisation
KM	Knowledge Management
KMPs	Knowledge Management Processes
KS	Knowledge Selection
LEEF	Lack of Extended Enterprise Function
LEKI	Lake of Environmental Knowledge Inventory
LFKI	Lack of Functional Knowledge Inventory
LIKI	Lack of Interactional Knowledge Inventory
LQDI	Low Quality Downstream Information
LQI	Low Quality Information
LQUI	Low Quality Upstream Information
MIO	Market Information Overload
MRP	Material Requirements Planning
PLS-SEM	Partial Least Squares Structural Equation Modelling
RELEV	Relevancy
SC	Supply Chain
SCAR	Scarcity
SCM	Supply Chain Management
SIO	Supplier Information Overload

SL	Shared Language
SME	Small and Medium-Sized Enterprises
T&A	Timeliness and Accuracy
TEO	Trustful Environment within Organisation
TRP	Trustful Relationship with Business Partner

Chapter 1 Introduction

This chapter introduces the research background and shape the research objectives and defines research questions. In addition, the research methodology adopted in the study is briefly introduced. The final section shows the thesis structure.

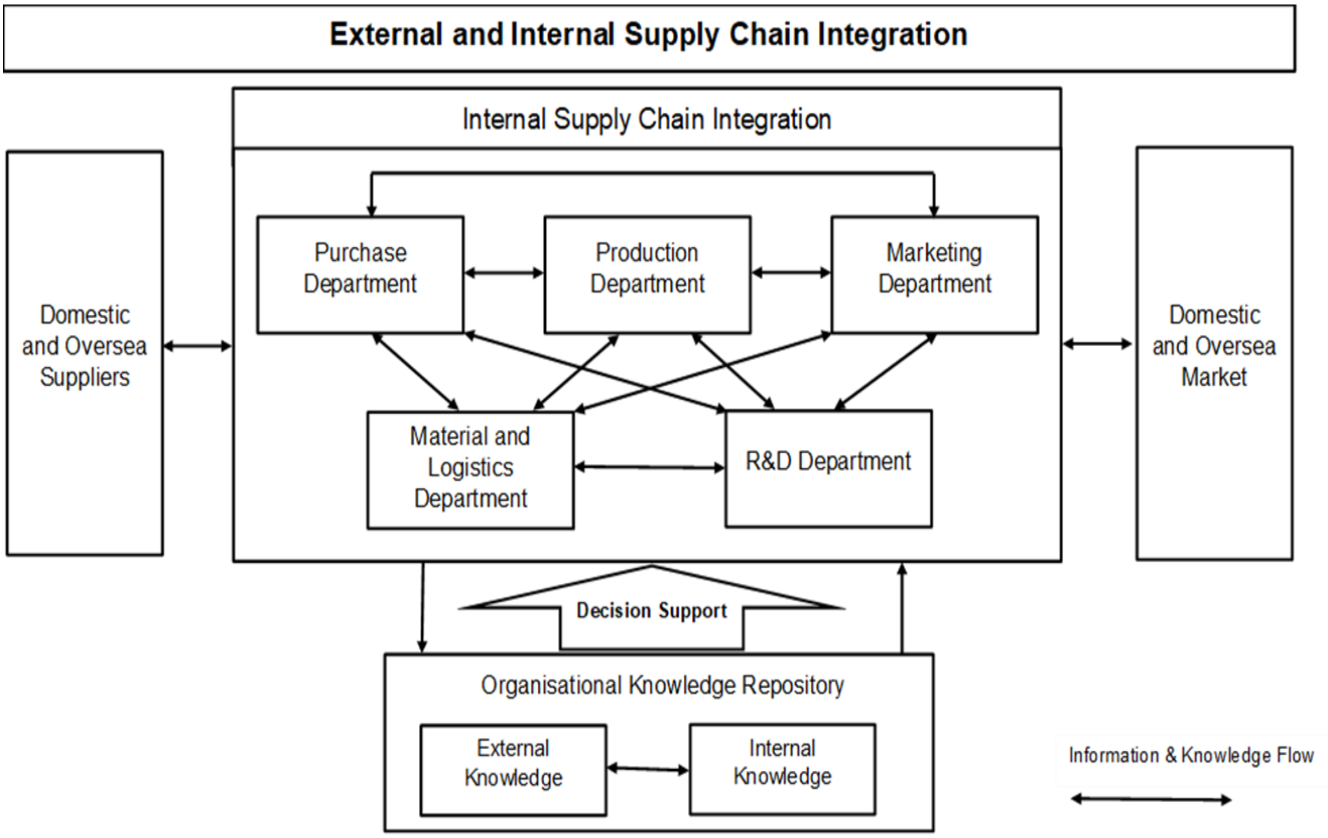
1.1 Research Background

Peter Drucker (2001), one of the world's most influential management guru, said that in the 21st century, the most valuable property of an organisation would be knowledge workers and their outputs. Today, more and more companies have realised that knowledge is their most valuable organisational resource from a strategic perspective and thus a foundation for competitive advantage (Erden et al., 2008). This helps to explain the growth of interest in the topic of knowledge management among academics and business practitioners (Hislop, 2009). Knowledge management is defined as the management of activities and processes that enhance the creation and use of knowledge within an organisation in order to ensure knowledge users have the knowledge and information they need in the right place and at the right time (Holsapple and Singh, 2001).

In the past decades, due to globalisation, rapid changes in customer demand and fierce market competition, it is not sufficient for a firm to restrict their vision to their own processes. To survive and be competitive, they must integrate their business partners to form a supply chain where all members with different roles or functions work together to source, produce and deliver goods and services to end customers. This is supply chain integration, which can be divided into internal and external integration (Chaudhuri et al., 2018; Schniederjans et al., 2020). Internal integration refers to the cooperation between different internal departments of a company, such as procurement, production, marketing, product design and logistics departments. Integration can break down functional barriers and facilitate sharing of valuable information and knowledge across these key departments (Moyano-Fuentes et al., 2016). External integration includes supplier integration and customer integration. Supplier integration implies strategic joint collaboration between a focal company and its suppliers in order to generate advantages, such as risk sharing, reduction of inventory and lead time. Their collaboration includes information and knowledge sharing, strategic partnership, collaborating in planning and product development (Wong at al., 2011; Moyano-Fuentes et al., 2016; Olsen, 2018). Customer integration can be considered as an interaction between a company and its customers, in which the customers become co-producers by joining in activities and processes that used to be the exclusive field of the manufacturing company. Together with the help of supplier integration, the focal company is able to establish closer relationships with key customers by keeping frequent communications and being highly responsive to their needs.

Supply chain integration seeks the synchronisation and convergence of intrafirm and interfirm operational and strategic capabilities into a unified, compelling market force, which then leads supply chain members to become mutually dependent and focus on jointly developing solutions to create value for customers. Although supply chain members are interdependent, their cooperation in the form of joint problem solving and synchronisation of activities remains difficult because they still are independent, separate entities (Pillai and Min, 2010). Therefore, the success of supply chain integration relies heavily on the support of smooth information and knowledge flow among members. Consequently, information and knowledge management play a critical role in achieving full integration of a supply chain. It supports a supply chain by providing the tools necessary to manage large amounts of information generated by supply chain operators and their customers. Supply chain managers need to understand, monitor and control operations in the entire supply chain, from sourcing, logistics, production and retail delivery to customers (Olson, 2018). All these tasks involve managing knowledge not only from the technology side through IT systems, but also by the quality and quantity of knowledge provided in the supply chain through data management and analytics (Schniederjans et al., 2020). **Figure 1-1** depicts how data, information and knowledge flow among different parties of internal and external of a manufacturing company to support its supply chain integration.

Figure 1-1: How Knowledge Flow Support Supply Chain Integration and Decision Making



Source: The Author (2020)

Despite the fact that the role of knowledge management (KM) in supply chain management is established in current literature, how to use an holistic approach to improve KM performance for a manufacturing supply chain has yet to be fully explored, as most related studies mainly focus on improving one or two elements of KM aspects. In fact, KM is a multi-dimensional domain. It contains many activities and processes (which are discussed deeply in the literature review in Chapter 2), these processes are linked together and could influence each other. Only focusing on improving one aspect of KM may make the effort in vain. Therefore, it is necessary to find a comprehensive approach to improve overall KM performance.

Lean thinking has been successfully implemented in almost all types of manufacturing industries worldwide for more than twenty years. Its purpose is to eliminate wastes (i.e. inefficient activities or processes) in all aspects of a business, such as reducing overproduction and unnecessary inventory, eliminating inappropriate processes and movement, as well as reducing defects and waiting time. It is a comprehensive approach. By clearly outlining all production and logistics operations, companies are able to distinguish all value-adding and non-value-adding processes. Non-value-adding processes should be improved or eliminated so that the overall production process can be improved. Therefore, a question arises: is it possible to use Lean thinking to improve KM performance of manufacturing supply chains? This question leads to the following research aim and objectives.

1.2 Research Aim, Objectives and Questions

The aim of this research is to eliminate inefficient knowledge management activities and use Lean Principles as guidance to improve knowledge management performance in manufacturing supply chains. The key output is a model for Lean-Knowledge Management Processes (Lean-KMPs). To realise the above overall aim, five objectives are set:

1) To identify the major activities of knowledge management processes in the manufacturing supply chain context.
   In order to improve supply chain knowledge management performance, it first needs to understand what knowledge management is about, and then identify the major KM activities or processes involved. By enhancing each KM activity, the overall KM performance can be improved. To

address this objective, a comprehensive literature review concerning KM processes and lifecycle has been conducted.

2) To use Lean thinking to distinguish inefficient and efficient knowledge management activities based on the manufacturing supply chain context. Similar to the first objective, a systematic literature review has been carried out. It helps the researcher to fully understand the Lean thinking and discover its possible application in supply chain knowledge management, which is to identify possible inefficient and efficient KM activities in manufacturing supply chains with the Lean thinking.

3) To examine the effects of Lean-KM Wastes on the knowledge management processes of manufacturing supply chains.
   To address this objective, the study tests the effects of the four Lean-KM Wastes (inefficient KM activities) on KM processes.

4) To examine the effects of Lean-KM Principles on knowledge management processes of manufacturing supply chains.
   This objective is fulfilled by testing the effects of the two Lean-KM Principles (efficient KM activities) on KM processes.

5) To develop and test the conceptual model of Lean-KMPs in different contexts.
   The last objective is addressed by testing the Lean-KMPs model developed in this research with pair-wise comparisons of three groups (i.e., two countries, two types of manufacturing industries, and two types of business sizes).

To address the research objectives, five specific research questions were developed:

RQ1. What are the major dimensions or activities of knowledge management in the manufacturing supply chain context?

RQ2. What are the Lean Wastes that could suppress knowledge management processes in the manufacturing supply chain context?

RQ3. What are the Lean Principles that could enhance knowledge management processes in the manufacturing supply chain context?

RQ4. How and to what extent do Lean Wastes influence knowledge management processes in the manufacturing supply chain context?

RQ5. How and to what extent do Lean Principles influence knowledge management processes in the manufacturing supply chain context?

RQ6. Are there any significant differences when the Lean-KMPs model is applied in different contexts: two countries (China vs. the US), two types of industries (machinery and electronics manufacturing vs. food and drink), and different company sizes (SMEs vs. large companies)?

1.3 Research Justification

Many Lean knowledge management related studies were conducted in knowledge-intensive industries such as service and high-tech industries, most of which mainly focus on adopting Lean thinking within an organisation or a project to improve KM through optimised IT systems and effective personnel management. More studies of manufacturing-oriented Lean KM are needed. Therefore, in order to fill the gap, this research brought the Lean thinking back to its origin (i.e., manufacturing industries) to enhance their KM performance. It covers all aspects of manufacturing operations including IT systems, personnel management, product design, manufacture, decision and strategy making, planning, problem solving, forecasting, marketing, and coordination and cooperation between supply chain partners.

In addition, the literature review highlighted the relative lack of a comprehensive approach for improving the whole knowledge management processes. Instead, existing studies mainly focused on using Lean thinking to improve companies' knowledge sharing or knowledge generation related activities. In order to fill this gap and answer RQ1, five knowledge management processes (i.e., knowledge acquisition, knowledge selection, knowledge generation, knowledge internalisation, and knowledge externalisation) were identified and five corresponding constructs as well as 30 indicators were developed through a rigorous literature review. The purpose is to use Lean thinking to improve every aspect of knowledge management. Moreover, since this is a new research direction, it is necessary to develop Lean-KM practices specifically for manufacturing industries. In order to identify what Lean-KM practices include and to test how and to what extend they could impact on KMPs in the context of manufacturing industries, 4 Lean-KM wastes and 2 Lean-KM Principles were developed in this research. Moreover, 20 sub-factors and 75 corresponding indicators were also developed so as to accurately measure the Lean-KMPs model and enrich the theoretical concepts. Therefore, the results of this research have the potential to deliver considerably greater benefit for improving knowledge management performance of manufacturing supply chains.

1.4 Research Scope and Method

To achieve the research aim and objectives, this study utilised quantitative methods. Observed variables derived from latent constructs are explored and selected based on rigorous literature review, in-depth discussions, item review, and pilot study with experts to avoid ambiguity or misunderstandings in the instruments (i.e. questionnaire) and to suggest modifications.

Survey based quantitative data were obtained from the top, senior and middle managers from SMEs and large manufacturing companies engaged in machinery and electronics manufacturing industry, and food and drink industry in the USA and China. The reasons for this sampling decision are, firstly, comparing with staff in a lower position, these people usually have longer working experience, sufficient knowledge and more comprehensive view with regard to the research topic, so they are more likely to be able to provide accurate answers to the questionnaire. Secondly, the two types of industries are two major components of light industry and heavy industry, respectively. Hence, they have good representativeness for manufacturing industries. Thirdly, the USA and China are two big manufacturing countries in the world. Hence, the sample drawn from these two countries can be considered as good representation of the manufacturing industries in the world (Rhodes, 2018). In addition, 38 usable questionnaires were also collected from the UK in case of a low response rate in the former two countries. Since the sample size was too small, the responses from the UK will not be adopted in multi-group analysis for national comparison but will be used for the rest of the analyses.

The hyperlink of the online questionnaires was emailed and texted to potential respondents. This data collection method is inexpensive to create and collect, eliminates the risk of missing data, and facilitates the data entering process for data analysis (Saunders et al., 2016). To increase response rates, respondents were promised to be offered anonymity and an executive summary of findings. Online questionnaires were distributed from April to October 2018. In total, 359 usable sample were collected.

In the stage of data analysis, SPSS software (version 24) was used to identify outliers to make sure the data were reliable and valid. Subsequently, a partial least squares structural equation modelling (PLS-SEM) approach was employed to test the research hypotheses. This approach has the ability to provide robust results and achieve higher statistical power when assessing research models with a relatively small sample size (Hair et al., 2017). It also can handle more complex models (i.e., a large number of both endogenous and exogenous latent variables with two to three layers of hierarchy). PLS-SEM was carried out to examine the relationships between these variables using SmartPLS statistical packages (version 3.0), since this software is very strong at analysing multiple relationships simultaneously. It is also very easy to use so that researchers can be more focused on their research without taking too much time on learning the software.

1.5 Structure of the Thesis

The thesis comprises eight chapters. These are detailed below:

Chapter 1 provides a brief overview and justification of the study. It highlights the study's background, the research aim, objectives and questions, as well as the research scope and method and the structure of this thesis.

Chapter 2 outlines the extant literature in regard to supply chain knowledge management, knowledge management processes, Lean thinking and Lean knowledge management. Then, the chapter highlights the limitations of the previous studies in Lean thinking and knowledge management to identify the research gaps and select areas needing further research.

In *Chapter 3*, based on the literature review, a conceptual model of Lean-KMPs and the two main research hypotheses and nineteen sub-hypotheses are developed for empirical testing. In addition, each construct in the model is conceptualised and operationalised to underpin the online questionnaire deployed in this study.

Chapter 4 discusses the research methodology adopted in this research for answering the research questions and achieving the research objectives. It presents the research philosophy, approach, design, survey method, data analysis method, sampling design, and research ethics implemented in this study along with the justifications for selecting them.

Chapter 5 outlines the data collection procedures used for collecting empirical data for testing the proposed conceptual model. It discusses the steps taken to collect the data, which includes structuring the survey questionnaire, selecting scale items to measure the underlying latent variables, the questionnaire translation method, pilot testing of the questionnaire, and survey constraints.

Chapter 6 devotes to the hypothesis testing for this research. Firstly, it displays the descriptive analysis based on the online survey to provide a general picture of the respondents' profile. It also incorporates consideration of missing data, suspicious response patterns, outliers, and data distribution. Secondly, the proposed research model and hypotheses were tested through PLS-SEM. Lastly, three pairs of multi-group analyses were conducted so as to identify the differences when the Lean-KMPs model is applied in different context: two countries (China vs. the US), two types of Industries (machinery & electronics manufacturing vs. food & drink), different company sizes (SEMs vs. large companies).

Chapter 7 discusses the empirical findings. It also explains the differences between the findings and the conceptual theories.

Chapter 8 concludes the thesis by highlighting the contributions to new knowledge. The theoretical and managerial implications are presented for academics and practitioners in the manufacturing supply chain. Finally, this chapter details the limitations, recommendations, and directions for future studies.

1.6 Summary

This chapter provided an overview of the contents of this thesis by including research background, research aim, objectives and questions, research methodology and the structure of the thesis. The next chapter presents the literature review on knowledge management, Lean thinking, and its application in KM processes.

Chapter 2 Literature Review

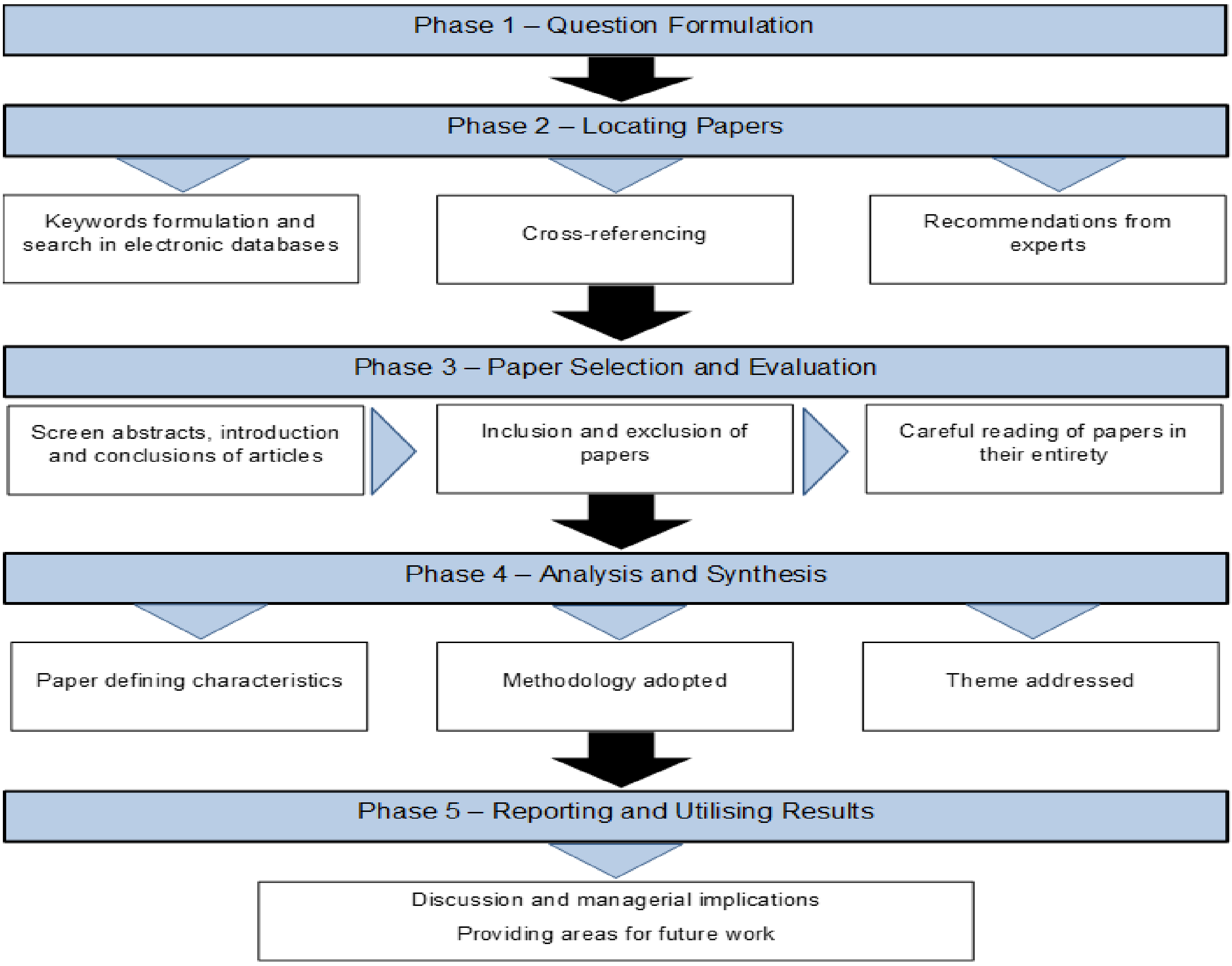
This chapter discusses the theoretical foundations of this study, starting with an explanation of the literature review method. The next section reviews past research studies carried out on knowledge management (KM) implemented in the context of manufacturing supply chain from three main aspects, which are firstly, the definition of data, information, and knowledge as well as the relation between them; secondly, knowledge components such as knowledge types, knowledge flow and knowledge management for manufacturing supply chains; and thirdly, the KM lifecycle or KM processes which is the embodiment of KM is also explained. Lean thinking is discussed in the third section of this chapter, which covers two main aspects: classic Lean Thinking in the manufacturing industry; and a review of several milestone research papers with regard to the application of Lean Thinking to knowledge management. This section ends with the identification of Lean Wastes and Lean Principles in knowledge management processes. Research gaps are then identified as the justification for this research.

2.1 Review Method

Systematic literature review (SLR) has been adopted as the main review method for this research. SLR "*integrates a number of different works on the same topic, summarising the common elements, contrasting the differences, and extending the work in some fashion*" (Meredith, 1993, p.8). SLR is a valuable method for understanding a topic, detecting gaps in the existing literature, developing propositions and discussing future research implications (Carter and Rogers, 2008). The SLR method has been widely used to consolidate emerging topics, such as the application of Lean Thinking in information management (Redeker et al., 2019), and the role of knowledge management process and knowledge configurations in improving business performance (Mahdi et al., 2019; Mejri et al., 2019).

As illustrated in Figure 2-1, SLR follows a five-step process to avoid bias during the research and ensure replicability. These steps are described in detail in the following sub-sections.

Figure 2-1: SLR Processes



Sources: Denyer and Tranfield (2009); Hofmann and Bosshard (2017)

Phase 1 -- Question Formulation

Setting a clear focus is the first step in an in-depth literature review (Light and Pillemer, 1984). Therefore, the researcher has rigorously defined review questions, which have to be well specified, informative and clearly formulated to avoid ambiguity (Melacini et al., 2018). The literature review focused on the following review questions that were developed based on the first three research questions in Chapter 1:

Q1. What is knowledge management and what are the elements involved in it?

Q2. What is Lean thinking and how can it be integrated into knowledge management to improve the knowledge management performance of manufacturing supply chains?

Phase 2 -- Locating Papers

The purpose of searching through relevant literature is to create a comprehensive list of core contributions related to the review questions (Denyer and Tranfield, 2009). In order to have a comprehensive review, the searching process covered four databases and avoided limiting any timeframe, specific journal or publishing outlets. More specifically, the selected databases include Emerald, Science Direct, Scopus, and Wed of Science, as they have the largest business research repositories. In addition, as suggested by Marchet et al. (2014), the researcher also selected academic articles or reports through cross-referencing and recommendations from supervisors, colleagues and experts. Furthermore, keywords/search strings were used as the search criteria, meanwhile, Boolean search operators, such as "AND", "OR", and "NOT" were employed to combine different terms. For example, since the aim of the review questions is to search the knowledge management processes and the application of Lean thinking in supply chain knowledge management, the researcher used a combination of terms related to three areas (e.g., "supply chain" AND "knowledge management" AND ("Lean thinking" OR "Lean wastes OR Lean principles"), with all related terms), searching for them in the title, keywords and abstract.

Phase 3 -- Paper Selection and Evaluation

The initial literature database was established by the keyword search. The next step was to distinguish between relevant and irrelevant papers through the careful analysis of abstracts, introductions and conclusions (Melacini et al., 2018). The inclusion criteria employed were:

- Availability – Full text articles
- Types of articles – Theoretical and conceptual studies. High-quality conference papers.
- Peer reviewed articles.
- Relevance – Articles could help to answer the formulated review questions. Articles used solid data collection and analysis methods, as well as demonstrate clear contribution to new knowledge.
- Language – English

After the rigorous selection and evaluation processes, the remaining articles were credible and relevant to the research topic. Subsequently, after careful reading all selected articles entirely. Moreover, by cross-referencing all the citations and bibliographies, several potential contributions were identified.

Phase 4 -- Analysis and Synthesis

All selected papers for this research were recorded in a Microsoft Excel spreadsheet and individually categorised for further analysis. The categorising process was based on the following criteria:

- Defining characteristics: year of publication, title, country, publication platform.
- Methods adopted: there were five types of research methods, which include: surveys, modelling papers, theoretical and conceptual papers, case studies/interviews, and literature reviews (Winter and Knemeyer, 2013; Melacini et al., 2018).
- Themes addressed: most importantly, the collected papers were categorised into different groups based on the focus of each study and the key issues investigated. Two main themes were identified, and each contains several sub-components:

1) Supply chain knowledge management, knowledge flow and knowledge management components.
2) Lean thinking and its application in knowledge management.

Phase 5 -- Reporting and Utilising Results

After examining all the selected papers, the useful knowledge was elaborated to answer the two review questions in Phase 1 and the new promising research streams emerged.

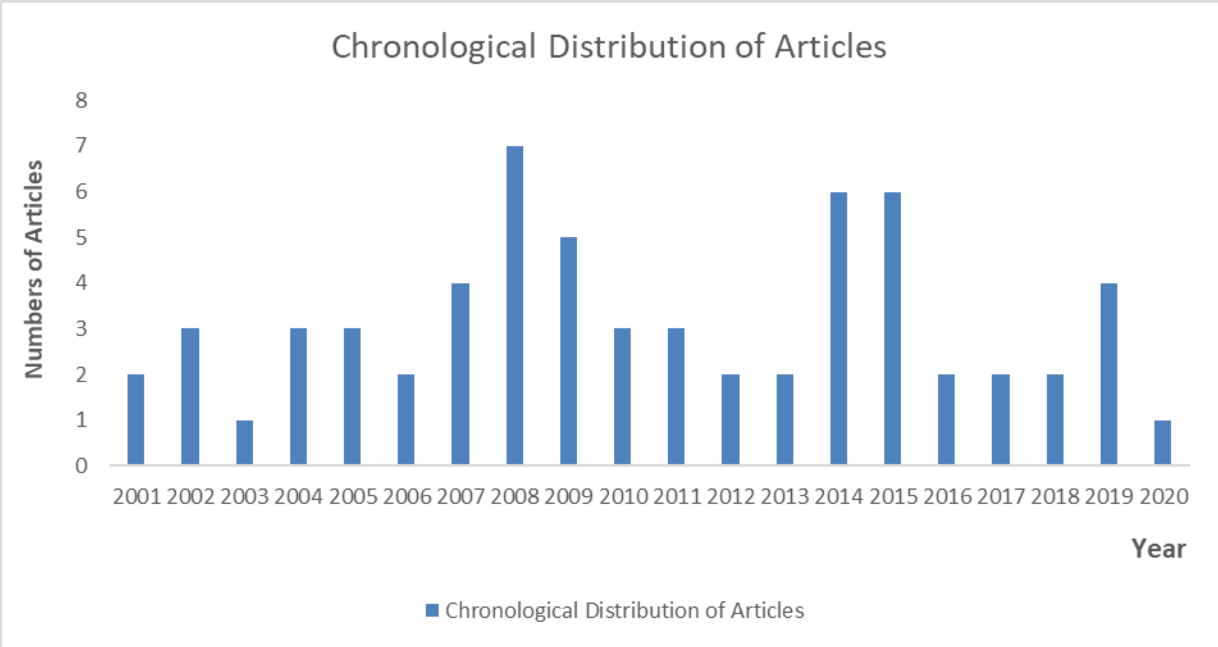
2.2 Descriptive Analysis

Initially, there were around 622 articles found in different databases. After the rigorous processes of selection and evaluation mentioned in section 2.1, 63 contributions remained as they are highly relevant to the research objectives, which are listed in Appendix A, these articles establish the theoretical foundation of this research. The aim of the descriptive analysis is to describe the attributes of all selected articles including the years of publication, countries, and the research methods adopted.

2.2.1 Time Span Analysis

The chronological distribution of the reviewed articles is shown in **Figure 2-2**, which illustrates the research tendency. It can be seen that all the relevant articles span the period from 2001 to 2020. The first journal papers about knowledge chain and Lean information/knowledge management (i.e., the primary focus) was published in 2001 and 2002, respectively. The number of articles fluctuates over the years since academics and practitioners have studied the application of Lean thinking in information/knowledge management from many different angles (sub-topics). These sub-topics has been used as the foundation to establish the conceptual model (i.e., Lean-KMPs) and latent constructs (i.e., 5 KMPs, 4 Lean-KM Wastes and 2 Lean-KM Principles) for this research.

Figure 2-2: Chronological Distribution



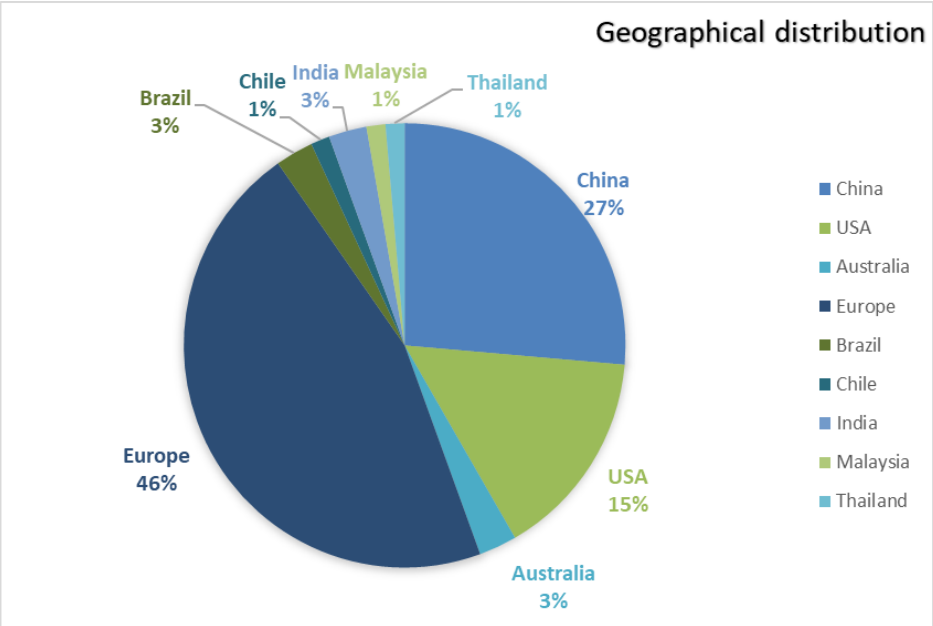
Sources: The Author (2020)

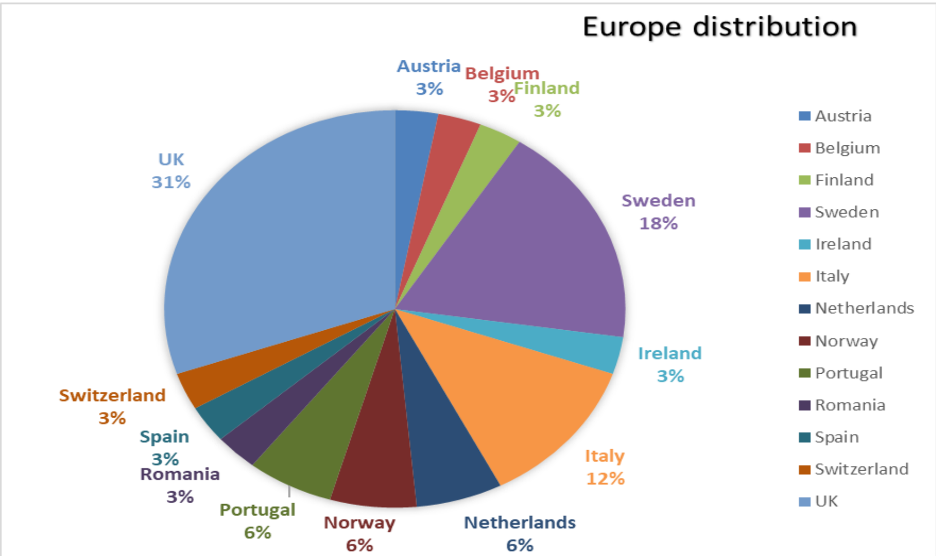
2.2.2 Geographical Distribution

The geographical distribution of publications offers another approach to gain an insight into the development of Lean knowledge management, since different countries have their own unique cultural characteristics and economic conditions, which could affect their KM development levels differently.

Figure 2-3 illustrates that the majority of the relevant papers are published in Europe, China, and the USA, which accounted for 46%, 27% and 15%, respectively. In terms of the European countries, the UK contributes 10 articles, Sweden contributes 6 articles, Italy contributes 4 articles, which take up 31%, 18%, and 12% of the whole European contributions, respectively. The reason why China, the USA and Europe have published the most papers is these countries are very advanced in technology, service, and manufacture, KM and Lean thinking as tools for gaining competitive advantages in these areas have already been widely and adequately implemented for many years. In addition, it is noticeable that some new emerging manufacturing and service countries, such as Brazil, India, Malaysia, and Thailand, published a small number of articles as Lean knowledge management is still a relative new topic to these countries. However, it can be foreseen that studies in this field will attract more attention in these countries as the implementation of Lean-KM will be one of the key determinants to enhance manufacturing companies' competitiveness.

Figure 2-3: Geographical Distribution



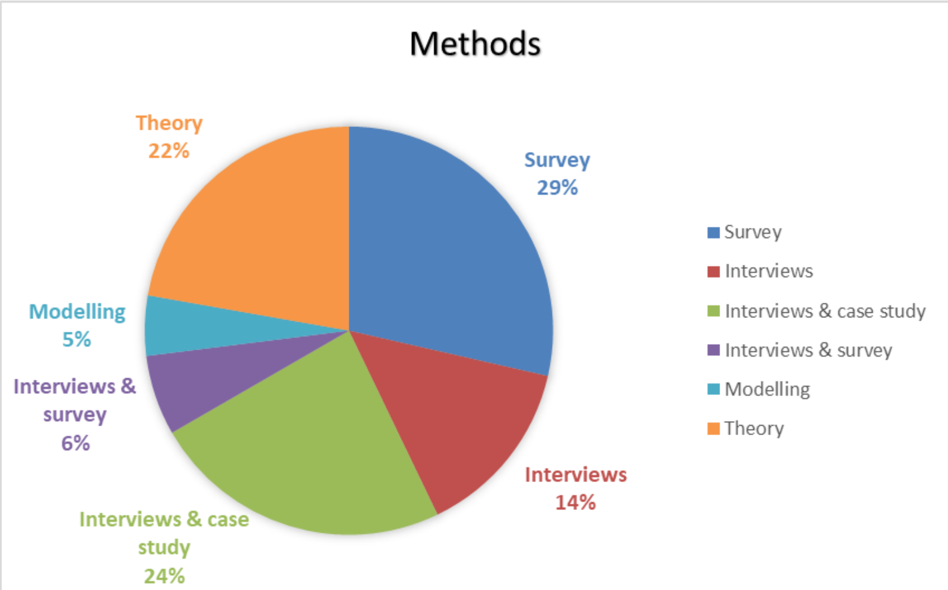


Sources: The Author (2020)

2.2.3 Research Methods

Figure 2-4 illustrates six research methods have been adopted in these selected articles to study Lean knowledge management. Survey, case study, and theory are the dominated methods, which accounted for 29%, 24% 22% of all relevant papers, respectively. Interview is also a common method adopted in these articles.

Figure 2-4: Research Methods



Sources: The Author (2020)

2.3 Knowledge Management

This section discusses the fundamentals of knowledge and knowledge management based on the context of manufacturing supply chain. First it defines data, information and knowledge and explains their differences and the relationships between them. Second, it illustrates the knowledge components required for KM, which are knowledge types, knowledge flow and knowledge management for manufacturing supply chains. Finally, the KM lifecycle, also known as KM processes, are critically discussed.

2.3.1 Data, Information and Knowledge

Before beginning to talk about KM, it is necessary to start by clearly defining the meaning of the world “knowledge”. It is also important to understand what constitutes knowledge and what the difference is between data, information and knowledge. Within different field of research many researchers have developed definitions for data, information and knowledge (Court, 1995; Hicks et al., 2002; Buchanan and Gibb, 2007; Liu, 2020). Data can be numbers, letters, signs or a combination of these three elements. It also includes non-text information, such as voice and image (Huang et al., 1999). It is the first form of knowledge (Uchitha, 2015). When data is processed, analysed, and structured with meaning it becomes information (Liu, 2020). In everyday routine, information guides and informs individual and organisational decision-making processes. When effectively managed and processed, information facilitates the generation of intellectual capital which underpins innovation and growth (Buchanan and Gibb, 2007). With respect to knowledge, it can be regarded as a high value form of information or actionable information that is ready to be applied to decisions and actions. It is a mixture of experience, values, contextual information and expert insight that provides a framework for evaluating and incorporating new experience and information (Davenport and Prusak, 2000, Jashapara, 2011). In the business world knowledge has been viewed as the most valuable commodity or intellectual asset, that is embedded in employees and businesses and delivered in the form of services and products (especially high-tech products) (Liu, 2020).

However, it should be noticed that, in practice, the terms information and knowledge are often used synonymously (like data and information). Business managers differentiate between knowledge and information intuitively and describe knowledge as information that has been processed and combined with context and experience. Therefore, sometimes, the boundary between knowledge and information is blurry, and depends on the users’ context (Nonaka and Konno, 1998). Knowledge to one given person for a certain task at a certain time may be only information or data for another task or at a different time (Holsapple, 2003). Hence, throughout this research the terms “information” and “knowledge” have been used interchangeably.

2.3.2 Knowledge Components Required for KM

Different Types of Knowledge in the Context of Manufacturing Supply Chains

In the context of business, supply chain knowledge can be regarded as the repository of collective insights, understandings, beliefs, behavioural routines, procedures and policies. They are drawn from hard data as well as on viewpoints, beliefs, values and intuitions. They are owned by the supply chain members for solving issues of mutual interest such as processes, technologies, products, and markets (Johnson et al., 2004; Pillai and Min, 2010; Li et al., 2012). Supply chain knowledge is presented in different forms such as forecasts, product design, competitor analysis, demand analysis, customer analysis and solutions to specific problems. (Tseng; 2009; Li et al., 2012; Liu et al., 2014a).

Supply chain knowledge types have been extensively discussed in the literature. For example, Johnson et al. (2004) examined how supply chain knowledge repositories affect supply chain partnership. They classified supply chain knowledge into three categories including:

1) *Interactional knowledge* consists of knowledge about issues related to interactions in business partner relationships. It includes aspects such as communication, negotiation, conflict management, and development and implementation of cooperative programs.
2) *Functional knowledge* consists of a company’s knowledge about issues related to the management of supply chain functions. It includes working with business partners in areas such as cost reduction, quality control,

operations and production, logistics and delivery, and inventory management, as well as product development.

3) *Environmental knowledge* consists of knowledge about a firm's external operating environment. It includes factors in the secondary and macro task environments, such as competitive behaviours, market conditions, and issues in laws and regulations.

Tseng (2009) proposed a conceptual framework to illustrate how an enterprise obtains knowledge from its supply chain to enhance its competitiveness. Three types of knowledge were also identified in this research, namely:

1) *Customer knowledge* is a company's experience and knowledge accumulated by long-term interactions with its customers. It includes customers' personal information, trading data, preferences and product feedbacks. Customer knowledge can help the company to fulfil customer demand and increase the capacity for product innovation.
2) *Supplier knowledge* is derived from the upstream manufacturers in a supply chain. This type of knowledge consists *inter alia* of information about suppliers' production and delivery capacity, research and development ability, and public relations. This not only helps a company to evaluate its suppliers, but also helps the company to improve product development and optimise its inventory level by linking customer demands with supplier capabilities, so that mistakes can be avoided and costs reduced.
3) *Competitor knowledge* is defined as knowledge of competitors' scale and quantity, threat level, manufacturing facilities and methods, research and development ability, and marketing strategies. It determines the ability of a company to evaluate its competitors and helps the company to develop the right counterstrategies.

Liu et al. (2014a) proposed a KM framework that identified and prioritised critical knowledge in order to support integrated decisions for global supply chains. They identified three types of global context knowledge, namely:

1) *Global market knowledge,* which includes knowledge for, from and about markets in relation to suppliers, customers and competitors. Business decision makers can use this knowledge to better understand changes in markets in order to forecast market demand, find opportunities, determine which market to enter, identify potential customers and their preferences about products or services, create new distribution channels, and develop an effective overall competitive positioning.
2) *Global capacity knowledge* refers to knowing how to manage aggregated demand from different markets around the world, especially under demand uncertainty or fluctuations. Global capacity strategies closely depend on manufacturing strategies such as make-to-stock, assemble-to-order, make-to-order, or engineer-to-order. Hence, global capacity knowledge can provide decision makers with the knowledge about capacity, constraints and balancing of global supply chains in order to support strategic global capacity decisions.
3) *Global supply network configuration knowledge* is concerned with the shape and integration of the global supply network, the roles of each participant (dominant or weak partners), responsibilities of participants (source, make, deliver, use or return), procedure and consequences about joining or leaving the supply network, and network re-configuration to deal with the dynamics of other participants joining and leaving. Typical modes of participants in a global supply chain include exporting, licensing, franchising, offshore outsourcing, joint venture and wholly owned subsidiaries.

Mejri, MacVaugh and Tsagdis (2018) conducted a study of knowledge-intensive SME internationalisation in developing economies. They identified three types of knowledge which includes:

1) *Technological knowledge, which* gives firm-specific advantages in developing and adapting products and services. It also includes organisational awareness of technological change across the broader market, and the relative position of competitors, thus informing reaction to the change. Increasing the organisation's technological knowledge

repository will result in enhanced products and services, creating new opportunities both at home and abroad.

2) *Market knowledge* is specific to each host market, including knowledge of potential customers, distribution channels, institutions, legal and regulatory conditions, and risks. Increasing the organisation's market knowledge repository will reduce uncertainty and risk, assist in exploiting growth opportunities, and help to better respond to market needs.
3) *Internationalisation knowledge* is a firm-specific ability to understand and pursue multiple international opportunities. It assists in screening foreign markets, evaluating and managing business partners, and investment.

Even though these classifications of knowledge look quite different in expression, some common features identified from the past studies are that the types of knowledge are either internal or external to a manufacturing company. Internal knowledge consists of different types of knowledge needed for solving issues inside the company in operation or production related tasks. External knowledge includes the different types of knowledge necessary for solving issues in business partner relationships, and dealing with changes, threats and risks from the external environment of the company. However, it should be noticed that internal and external knowledge are not isolated from each other, but rather interrelating and supporting one another.

From Knowledge Flow to Knowledge Management in Manufacturing Supply Chain

The single existence of knowledge somewhere in the organisation does not make it a valuable organisational resource if it is not accessible to the related members in the organisation. Its value is embodied in the level of accessibility. Knowledge flow running through a supply chain can improve knowledge sharing and make the knowledge accessible to the members of the supply chain. It contains a series of processes, events, and activities through which data, information, and knowledge are transferred from one company to another (Mu et al., 2008). Therefore, the more fluently knowledge flows as the members in a supply chain maintain close links with each other, the more knowledge can be accessible, the more effectively does the supply chain operate, and the more value can be created (Pablos, 2004; Hult et al., 2004; Gu et al., 2005; Yoo et al., 2007; Mu et al., 2008). Knowledge flow is the important way for increasing the quantity of existing knowledge (Chang et al., 2001), because when knowledge is acquired through knowledge sharing and combined with the existing knowledge, new knowledge will be created (Dalkir, 2017; Liu, 2020).

Knowledge management is understanding the organisation's knowledge flows, and implementing knowledge-related activities such as acquiring, selecting, generating, internalising, and externalising knowledge in order to create value for an organisation (Brooking, 1999; Holsapple and Singh, 2001; Yew and Aspinwall, 2004). It is concerned with ensuring that the right data, information and knowledge are available in the right form to the right users and processors at the right time for the right cost (Holsapple and Singh, 2001). The role of effective management of knowledge is evident in producing innovation, reducing lead times, improving quality, and increasing customer satisfaction (Maqsood et al., 2007). Through KM an organisation's intangible assets can be better utilised to create value, with both internal and external knowledge being leveraged to the benefit of the whole supply chain. KM can improve communications within business partners, and provide more informed knowledge by sharing best practices, lessons learned, and the rationale for strategic decisions. The failure to capture and transfer supply chain knowledge leads to a risk of reinventing the wheel, wasted activity, and impaired supply chain performance (Shakerian et al., 2016; Lim et al., 2017). Hence, knowledge management is regarded as an essential cornerstone for a supply chain to develop sustainable competitive advantage in order to remain at the forefront of excellence in a level play-field market (Yew and Aspinwall, 2004; Slagter, 2007).

Knowledge Management Processes

The knowledge management process may also be referred to as the KM lifecycle or knowledge chain. It is a systematic process comprised of multiple phases (Sedera and Gable, 2010). Many researchers have developed different sets of phases based on their particular application. **Table 2-1** demonstrates the KM processes and the number of phases used by previous studies. The number of phases varies from 3 to 8, although all supply chain related studies which involve the KM process concept used some common underlying phases. They are: 1) acquisition--/--collection--/--capture; 2) selection--/--identification--/--organising; 3) creation--/--generation--/--innovation--/--adaptation; 4) retention--/--storage--/--retrieval--/--dissemination; 5) application--/--utilisation.

Table 2-1: Knowledge Management Processes/Phases

Author	Phases of KM processes	No. of phases
Stein and Zwass (1995)	Acquisition, Retention, Maintenance, Retrieval.	4
Allee (1997)	Collect, Identify, Create, Share, Apply, Organise, Adapt.	7
Wiig (1997)	Creation, Capture, Transfer, Use.	4
Argote (1999)	Share, Generate, Evaluate, Combine.	4
Lee and Yang (2000)	Acquisition, Innovation, Protection, Integration, Dissemination.	5
Alavi and Leidner (2011)	Creation (combined: acquisition, innovation, integration), Storage/Retrieval, Transfer, Application	4
Holsapple and Singh (2001)	Acquisition, Selection, Generation, Internalisation, Externalisation.	5
Bergeron (2003)	Creation / Acquisition, Modification, Use, Archiving, Transfer, Translation / Repurposing, Access, Disposal.	8
Cormican and O'Sullivan (2003)	Generation, Representation, Storage, Access, Transfer.	5
Cheung and Myers (2008)	Creation, Assimilation & Integration, Application.	3
Parry and Graves (2008)	Use, Create, Organise, Disseminate.	4

Sedera and Gable (2010)	Creation, Transfer, Retention, Application.	4
Candra (2014)	Creation, Retention, Transfer, Application	4
Mahdi et al. (2019)	Identification, Knowledge goals formulating, Generating, Storage, Sharing, Application	6
Liu (2020)	Building, Holding, Mobilisation, Utilisation.	4

Source: The Author (2020)

Among these diverse KM processes presented in **Table 2-1**, Holsapple and Singh (2001) knowledge chain model is the closest one to match those common features identified above. This model is probably one of the most influential knowledge management frameworks. Over the last two decades, many researchers have developed their own KM models by either modifying or adding elements to Holsapple and Singh's model (Shin et al., 2001; Wu and Liu, 2001; Zhang and Zhou, 2006; Khadivar et al., 2007; Tseng, 2009; Schiuma et al., 2012; Liu et al., 2014a; Jiang et al., 2014). Hence, it is also adopted in this research for representing the full knowledge management processes. Thus the knowledge chain model contains five phases: knowledge acquisition, knowledge selection, knowledge generation, knowledge internalisation, and knowledge externalisation. These five phases are not necessarily performed in any strict pattern, but rather there can be various sequences, overlaps, and iterations (Holsapple and Singh, 2001).

Knowledge acquisition

Knowledge acquisition refers to the way organisations identifying needed knowledge from external environment and transform it into a form that can be used to generate new knowledge. The principle feature of this stage is an increase in the amount of knowledge, such as from zero to existence through identification and capture (Liu, 2020). Sub-activities involved in acquiring knowledge include:

1) Identifying required knowledge from external environment.

2) Capturing the identified knowledge from external sources by extracting, and collecting knowledge that has sufficient reliability, relevance, and importance for the task.

3) Organising and transforming the captured knowledge into usable representations.

4) Transferring the organised knowledge to a processor that immediately uses it or stores it within an organisation for future use. Examples of knowledge acquisition include conducing an external survey, getting information and technical support from supply chain partners, sending employees to external training, purchasing data sets and patented processes, and gathering knowledge via competitive intelligence

(Holsapple and Singh, 2001; Holsapple and Joshi, 2002).

Knowledge selection

Knowledge selection means that organisations identify needed knowledge within their existing knowledge resources and provide the knowledge in the correct form to an activity that needs it (i.e. to an acquiring, internalising, generating, or externalising activity) (Holsapple and Singh, 2001; Mahdi et al., 2019). Sub-activities in selecting knowledge include:

1) Identifying required knowledge within the organisation's existing resources.

2) Selecting the identified knowledge from internal sources by extracting, collecting knowledge which has sufficient reliability, relevance, and importance.

3) Organising and transforming the selected knowledge into understandable representations.

4) Transferring the organised knowledge to a processor that immediately uses it or internalises it within an organisation for future use.

(Holsapple and Joshi, 2002).

Knowledge selection is similar to acquisition, the main difference is that it manipulates knowledge resources already existing in the organisation, rather than those in the external environment. Examples of knowledge selection include selecting qualified employees to participate in a product development team, or selecting an appropriate procedure for forecasting, extracting needed information from a repository database, or field observation in an organisation (Holsapple and Singh, 2001).

Knowledge generation

Knowledge generation is an activity where organisations create knowledge by discovering it or deriving it from existing knowledge (Holsapple and Singh, 2001; Daud and Yusuf, 2008). It reflects the ability of an organisation to create useful and new solutions and ideas for different aspects of the activities within the organisation, such as developing products and services, deriving demand forecasts, making decisions, plans and strategies, recognising or solving problems, inventing managerial practices and technological processes (Holsapple and Singh, 2001; Nonaka, 2007). Sub-activities involved in knowledge generation include:

1) Monitoring the organisation's knowledge resources and the external environment.

2) Evaluating selected or acquired knowledge for its utility for the generation task.

3) Producing knowledge from a base of existing knowledge by creating, synthesising, analysing, and constructing knowledge.

4) Transferring the generated knowledge for knowledge internalisation or knowledge externalisation (see below).

(Holsapple and Singh, 2001)

Knowledge internalisation

Internalising is an activity that alters an organisation's knowledge resources based on acquired, selected, or generated knowledge in order to refine and update its own knowledge inventory. Internalising knowledge is an ultimate activity in organisational learning (Holsapple and Singh, 2001). Sub-activities involved in internalising knowledge include:

1) Assessing the knowledge to determine its suitability for internalisation.

2) Identifying knowledge resources that are to be impacted by the new knowledge.

3) Depositing the new knowledge to the identified knowledge resources

(Holsapple and Joshi, 2002).

This involves modifying existing knowledge resources by refining or even restructuring them fundamentally. Examples of knowledge internalisation include knowledge sharing, in-house training, populating a data warehouse, posting an idea on an intranet, publishing a policy manual, broadcasting a new regulation, modifying organisational culture or infrastructure, and making experts' knowledge available by developing expert systems (Holsapple and Singh, 2001).

Knowledge externalisation

Externalising knowledge means using existing knowledge to produce organisational output for release into the environment. It transforms raw materials into products and services (i.e. embodiments of knowledge in outward forms) for external consumption (Holsapple and Singh, 2001). Sub-activities involved include:

1) Targeting the output. This is a determination of what needs to be produced for targeted markets or certain customers.

2) Producing the output by applying, embodying, controlling, and leveraging existing knowledge to produce product for the target. The product is a representation of the knowledge used to produce it.

3) Transferring the output by packaging and distributing the product to the targets in the environment. Examples of externalisation include providing services, manufacturing a product, developing an advertisement, and publishing a report

(Holsapple and Joshi, 2002).

It needs to be emphasised that the above five knowledge management phases are not just a one-off occurrence, but rather a knowledge spiral. New knowledge can be acquired from customers' feedbacks and competitors' reactions after the services and products have been launched to the targeted market (i.e. knowledge externalisation).

2.4 Lean Thinking and Its Application in KM Processes

For more than twenty years, Lean thinking has been studied and applied in global manufacturing industries. It was first developed in the Toyota Production System in 1950s. Later, due to its successful implementation, the system's distinctive practices (i.e. Lean Toolbox) were widely introduced to major auto manufacturing companies, such as GM, Ford and Chrysler. Now, however, companies that have adopted the system can be found in fields as diverse as aerospace, consumer products, metals processing, and industrial products (Spear and Dowen, 1999; Dora et al., 2013; Garre et al., 2017; Steen and Tillema, 2018; Kamble et al., 2019). The purpose of Lean thinking is to eliminate wastes in all aspects of a business, such as reducing lead time, space, energy, materials, stress and overburden, defects, pollution, and changeover, processing, and work times (Bicheno and Holweg, 2009). Lean thinking is also about value. Every activity or process of business should provide value to their customer. The end-customer should not pay for the cost, time and quality penalties of wasteful processes (Harrison and Hoek, 2008). By mapping process throughout the manufacturing and delivery operations, it is possible to sort value adding and non-value-adding activities. Non-value-adding activities are wastes which should be improved or cut out of from the process.

2.4.1 Lean Wastes

Within the context of manufacturing industry, there are seven types of wastes which were first identified by Ohno (1988) in Toyota and published in the book *Lean Thinking* by James P. Womack and Daniel T. Jones (1996). The seven wastes include:

1) *The Waste of Overproduction*: It happens when operations or production processes continue after they should have ceased. Overproduction creates unevenness of material flow, which is harmful for quality and productivity (i.e. produces too many unwanted goods). It also leads to excessive storage and lead times.
2) *The Waste of Waiting:* It takes place whenever time is not being used effectively. This type of waste affects goods, workers and customers, each spending time waiting. Waiting time should be saved and used for value-adding activities.
3) *The Waste of Transporting:* It means that goods and materials are transported from one process to the next without adding value to it. In general, unnecessary transport should be limited as it adds time and cost to the process during which no value is added, and handling damage can occur.
4) *The Waste of Inappropriate Processing*: It means a process that is incapable of meeting quality standards required by the customer or user, so it always makes defects. Extra operations such as reworking, reprocessing, handling or storage occur because of defects.
5) *The Waste of Unnecessary Inventory*: Inventory includes raw materials, work-in-progress and finished goods. Many companies need inventory to do business, a company cannot sell what it does not have. However, unnecessary inventory that is not directly required to fulfil current customer orders will require additional handling and space. Hence, it can also significantly increase extra processing and cost.
6) *The Waste of Unnecessary Motions:* It refers to the extra steps taken by employees and/or equipment to cope with inefficient layout, defects, reprocessing, overproduction or excess inventory. Such waste is tiring for the employees and adds no value to the product or service.

7) *The Waste of Defects:* Finished goods or services that do not meet customers' expectation, thus causing customer dissatisfaction. The longer a defect is undetected the more cost is added. Defects can be eliminated by the concept of total quality management (Harrison and Hoek, 2008; Aka et al., 2020; Francis and Thomas, 2020).

The classic seven wastes discussed above are applied from the organisation's perspective. Bicheno and Holweg (2009) proposed new seven wastes which are more focused on the customer's or user's perspective. Zhao et al., (2016) adopted these seven wastes and developed a conceptual model to improve the performance of a customer service department in a machinery manufacturer. These new seven wastes include:

1) *Delay* on the part of customers waiting for service, for delivery, in queues, for responses, or for goods not arriving as promised. Customers' time may seem free to the provider, but the organisation loses sales when they take custom elsewhere.
2) *Duplication*: Having to re-enter data, repeat details on forms, copy information across, or answer queries from several sources within the same organisation.
3) *Unnecessary Movement*: Queuing several times, lack of one-stop service, and poor ergonomics in the service encounter.
4) *Unclear Communication* and the wastes of seeking clarification, confusion over product or service use, wasting time finding a location that may result in misuse or the duplication.
5) *Incorrect Inventory:* out of stock, unable to get exactly what was required, and/or substitute products or services.
6) *Opportunity Lost* to retain or win customers, through failure to establish rapport, ignoring customers, unfriendliness and rudeness.
7) *Errors* in the service transaction, product defects in the product-service bundle, lost or damaged goods.

2.4.2 Lean Principles

In addition to the classic seven Lean Wastes of Industry, Womack and Jones (1996) defined the five Lean principles which are used to guide the implementation of Lean thinking in manufacturing industry. The classic five Lean principles include:

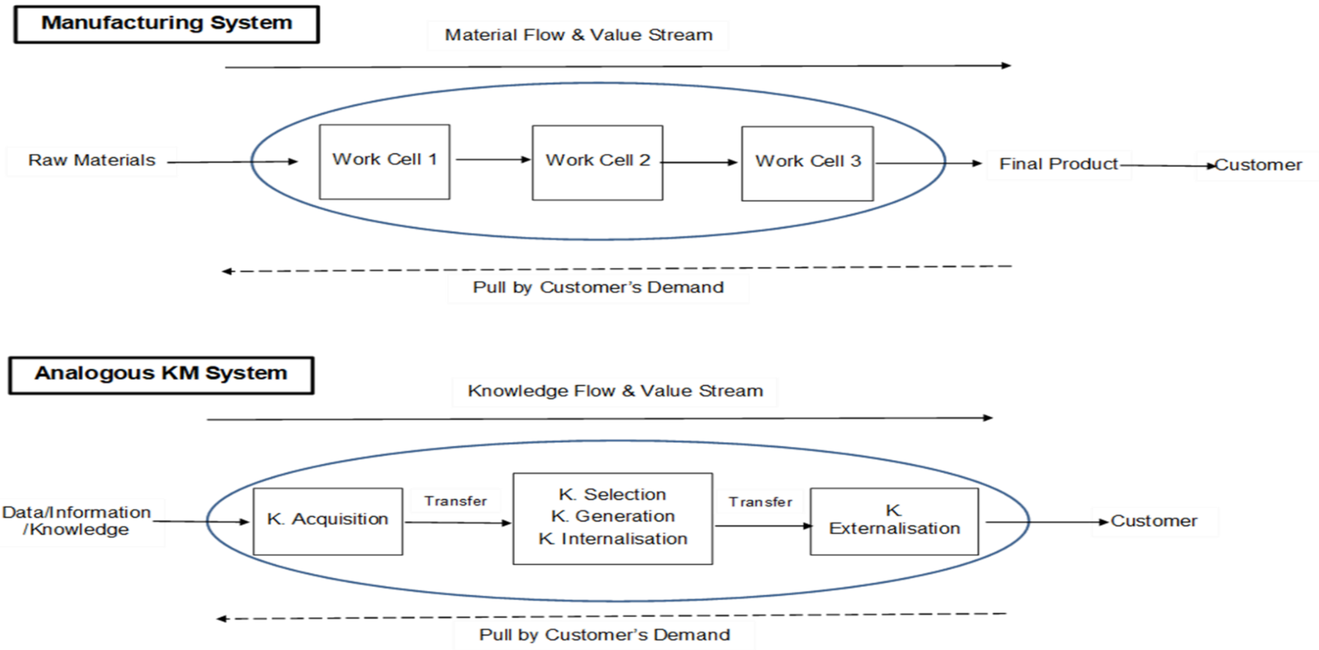
1) *Specifying Value*: Value is specified from the ultimate customers' or users' perspective. From the end-customer perspective, value is added along the supply network as raw materials from primary manufacture are progressively converted into the finished product bought by end-customers. Value can also be added in support activities, such as designing the products, and distribution and service processes needed to underpin the production activities (Womack and Jones, 1996; Harrison and Hoek, 2008).
2) *Identifying the Value Stream: "The value stream is the set of all the specific actions required to bring a specific product (whether goods, a service, or, increasingly, a combination of the two) through the problem solving task from concept through detailed design and engineering to production launch, the information management task running from order-taking through detailed scheduling to delivery, and the physical transformation task proceeding from raw materials to a finished product in the hands of the customer"* (Womack and Jones, 1996, p.9)
3) *Making value flow:* Once value has been precisely specified, and the value stream for specific product processes fully mapped by the Lean enterprise, then the company should minimise delays, inventories, defects and downtime to support the flow of value in the supply chain (Womack and Jones, 1996; Harrison and Hoek, 2008).
4) *Pull:* It means that no one upstream should produce goods or services until the downstream customer asks for it. This implies that demand information is made available across the supply chain. If it is possible, supply is from manufacturing, not from stock. If it is possible, customer orders are used for planning manufacture, not forecasts (Womack and Jones, 1996; Santhiapillai and Ratnayake, 2018).

5) *Perfection and Continuous Improvement:* There is no end to the process of reducing time, space, cost and mistakes. The Lean enterprise must regularly review operation processes and infrastructure. When business processes, infrastructure, and processes that support products and services change, it is an opportunity for new review and improvement (Hicks, 2007; Gong and Blijleven, 2017).

2.4.3 Lean Thinking in Knowledge Management

As previously stated, in principle, the concept of Lean can be applied not only in many different types of manufacturing sectors, but also in other aspects of the business, such as transportation (Sternberg et al., 2013), construction (Pheng and Fang, 2005; Sarhan et al., 2018; Tezel et al., 2018; Li et al., 2020), and agriculture (Chen et al., 2017; Melin and Barth, 2018). However, since the knowledge work environment is very different from the physical work environment, Staats et al., (2011) questioned the classic Lean thinking's universal applicability. Hicks (2007), Iuga et al. (2015) and Redeker et al. (2019) disagree with this opinion and argued that the concept of Lean thinking (i.e. the removal of waste and pursuit of perfection) can be applied to any system where product flows to meet the demand of the customer, user or consumer. These elements are very similar to information and knowledge management where information flows and work are undertaken to add value to the information and knowledge to meet the demand of the knowledge user. A value flow model as applied to a manufacturing system is presented in **Figure 2-5** which also depicts the analogous model of value and flow for information and KM systems. This analogous value flow model for knowledge management can be applied to any knowledge processing activity. For example, the processes of explicit data generation for operational decision-making, or the acquisition and management of information records for knowledge repository. In these two examples, there is an intrinsic value in the data itself, and added value is generated by the mechanisms by which the data and information is acquired, organised, selected, generated, exchanged, internalised, and externalised (Holsapple and Singh, 2001). In addition, these mechanisms and the information itself may generate or contain some type of wastes just as may happen in manufacturing systems (Zadeh et al., 2017).

Figure 2-5: The Value Flow Model for Knowledge Management



Source: Adapted from Hicks (2007).

Hicks (2007) and Staats et al. (2011) studied the knowledge work environment in software industry, they defined waste as contextual elements that undermine the efficiency of knowledge work, which include task uncertainty, process invisibility, and architectural ambiguity, and these elements make an environment where the flow of activities is jammed. Hicks (2007, p.238) defined waste within the context of information management as any "*additional actions and inactivity that arise as a consequence of not providing the information consumer immediate access to an adequate amount of appropriate, accurate and up-to-date information*". This definition is again analogous to the principles of Lean thinking in a manufacturing context. Therefore, the Lean thinking in the context of knowledge management is to eliminate wastes and improve the flow of value (i.e. Lean Principles) in order to identify and enable focused improvements on the various aspects of knowledge management previously defined (Soare and Teixeira, 2014). The improvements can be seen, in the case of the manufacturing sector, in the efficiency, productivity and quality of the overall process (knowledge management) and product (data, information and knowledge). All of which support an organisation's core activities and sustain its long-term competitiveness (Psomas, 2018). Therefore, from what has been discussed above, it can be concluded that the concept of Lean can be applied to any information and knowledge processing activity. Indeed, in the past 10 years, various researchers reported that Lean thinking is able to improve knowledge management in multiple service industries, including government (Radnor, 2010; Janssen and Estevez, 2013), healthcare (Dahlgaard et al., 2011; Yusof et al., 2012; Toussaint and Berry, 2013; McDermott and Venditti, 2015; D'Andreamatteo et al., 2019), the banking industry (Gong and Janssen, 2015), customer services (Zhao et al., 2016), education (Kerdpitak and Jermsittiparsert, 2020); the construction industry (Zhang and Chen 2016), in technology innovation (Ismail et al., 2014; Amrit et al., 2015; Gong and Blijleven, 2017; Balocco, et al., 2019), and in product development (Santhiapillai and Ratnayake, 2018), as well as in manufacturing supply chain management (Liu et al., 2014b; Pan et al., 2014).

2.4.4 Identifying Lean Wastes and Lean Principles in Knowledge Management Processes

Central to successful Lean implementation is the understanding and characterisation of waste and value from the customer's (or end user's) perspective. However, due to the tangible nature of manufacturing as opposed to the intangible nature of knowledge, the classic seven Lean Wastes and five Lean Principles in the manufacturing sector cannot be directly adopted for Lean KM. For instance, manufacturing overproduction is very visible and its effect tangible. In contrast to this, where usable digital data and information are considered, the various dimensions of waste do not occupy an equivalent space, the effects are less tangible, and the value flow is far less clear and arguable highly subjective. Therefore, Hicks (2007, p.239) defined both *Wastes* and *Value* in the context of Lean knowledge management in order to facilitate their classification. Values of information "*depend upon whether the information supports decisions marking…and also whether it offers current value or potential value in the future*". Waste can be considered as the barriers to prevent information/knowledge flow and reduces information users' ability to access their required information and knowledge. These wastes may include the effort to overcome difficulties in retrieving or accessing critical information and knowledge, or the activities required to validate and correct low-quality information (e.g. to gather required information again and checking) (Redeker et al., 2019).

Based on the above two definitions, Hicks et al. (2006) conducted a series of case studies with 10 small to medium-sized engineering companies. Through an evaluation of 18 knowledge management core issues encounter by these companies, Hicks and his colleagues identified four fundamental causes of waste which give rise to four corresponding types of wastes. The four causes are:

1) Information that cannot flow because it has not been generated and identified.
2) Information is unable to flow because flow activation or shared processes are incompatible, or a critical process is broken or unavailable.
3) Excessive information or excessive information flows are generated and maintained, with the result that the most appropriate and accurate information cannot be easily identified.
4) Inaccurate information flows resulting in inappropriate activities, the need for corrective action or checking.

(Hicks, 2007)

The four types of waste include:

1) Failure demand: this includes the resources and activities that are necessary to overcome the lack of information. It may include the effort for generating new information and/or acquiring additional information.

2) Flow demand: refers to the time and resources spent trying to identify the information elements that need to flow.
3) Flow excess: relates to the time and resources that are necessary to overcome excessive information (i.e. information overload).
4) Flawed flow: refers to the resources and activities that are necessary to correct or verify information, it can also be caused by inappropriate process, or some critical process that was not available

(Hick, 2007; Redeker et al., 2019).

It can be noticed that Hicks's four knowledge management wastes are a partial analogy to the well-known classic Lean Wastes in manufacturing systems. *Failure Demand, Flow Demand, Flow Excess* and *Flawed Flow* correspond with *Inappropriate Processing, Waiting, Overproduction* and *Defect, respectively.* No correspondence can be found for transport, inventory and motion because the focus is on electronic information management systems. Hicks believes that digital data exchange and storage within the system happens almost instantly, and the cost is trivial.

Inspired by Womack and Jones (1996) and Hicks' (2007) Lean concept, Hölttä et al. (2010), Vergahen et al. (2015) and Santhiapillai and Ratnayake (2018) applied Lean thinking to knowledge management and created Lean KM models with the aim of improving operational performance for the automotive, heavy machinery production development and software intensive mechatronics industries. They categorised six types of wastes as shown in **Table 2-2.** Comparing with Hicks' (2007) four Lean Wastes, these six wastes classification are similar to the traditional seven wastes, but their concepts also have much in common with Hicks's Lean Wastes. In addition to these six types of wastes, Iuga et al. (2015) added one more type of wastes: "*Not involving the employee*" in their research for improving the selection of the key performance indicators (KPI) with Lean thinking. This type of waste highlights the importance of involving employees in KM, because a company's most valuable knowledge/experience, especially tacit knowledge, is embedded in their employees who can be considered as a type of knowledge repository. If the company does not make good use of this knowledge, they may lose it one day when the employee retires or leaves the company.

Table 2-2: Waste Categories in Lean KM

Waste Category	**Examples**
Over & under stock	• Excessive information. • Loss or lack of information. • Excessive documentation; unnecessary details.
Unnecessary motion & transfer	• Manual intervention due to the lack of integration between systems. • Information is handled by several people before arriving at the user, which causes errors, losses, duplication and redundancy.
Waiting	• Waiting for required information and knowledge • Information does not flow (waiting for intervention).
Unnecessary processing	• double handling (inappropriate handling process) • Inaccurate information; necessary corrective actions. • Increase in resources to process corrective action
Defect	• Flawed/inaccurate information. • Information formats (lack of common/compatible standards). • Information systems (problems in converting information).
Overproduction	• Excessive number of systems. • Multiple data sources (several systems with the same information).

Source: Adapted from Hölttä et al. (2010), Vergahen et al. (2015), and Santhiapillai and Ratnayake (2018)

In terms of Lean Principles, the traditional five Lean Principles proposed by Womack and Jones (1996) can also be applied to KM. The key principles of Lean KM, deeply described by Hicks (2007), are summarised in the following:

1) *Value*: information and knowledge must supply value to knowledge users.

2) *Value stream*: a series of processes and activities that deliver knowledge must be mapped. This includes processes that support the acquisition, selection, generation, internalising, and externalisation of information.
3) *Flow*: knowledge should be made to flow efficiently, particularly the most valuable knowledge.
4) *Pull:* knowledge should be delivered as it is requested or needed by knowledge customers.
5) *Continuous improvement*: perfection should be pursued by continually removing wastes and regularly reviewing the knowledge management system, that is creating a culture of continuous improvement.

2.5 Research Gaps

Based on the review of the related work in section 2.3 and 2.4 above, there are four clear gaps in the literature. Firstly, it is interesting that very few prior studies have tried to integrate Lean thinking with KM to improve manufacturing supply chain's KM performance, even though the Lean concept originated from the manufacturing sector. Most of the Lean-KM related studies reviewed in this chapter were conducted in service and high-tech industries, especially in health care, engineering and IT development (Redeker et al., 2019). One of the reasons which may explain this situation is that these are knowledge-intensive industries, and issues in their KM performance can be spotted relatively early and easily. Therefore, for the manufacturing supply chain context, Lean-KM is a new promising research stream.

Secondly, the review reveals a lack of common definition of Lean-KM for the manufacturing supply chain context. Although the Lean thinking or philosophy remains unchanged from manufacturing to KM, Lean-KM practices (i.e. Wastes and Principles) need to be tailored for this context. Without clearly defined Lean-KM practices or tools, Lean thinking cannot be applied to supply chain KM.

Thirdly, the review also highlights the relative lack of an overall frameworks for improving knowledge management itself. Instead, most of the approaches mainly focus on using Lean thinking to improve one or two elements of KM aspects, more specifically, on knowledge sharing or transfer and knowledge generation or innovation. Although these aspects are important, it is arguable that a more holistic or systemic approach (e.g. knowledge management processes) has the potential to deliver considerably greater benefit for the organization.

Finally, as most research on this subject are company-specific or project-specific following a case study approach, more rigorous industry-specific empirical studies and evidences are needed (Gupta et al., 2016). These research gaps are addressed in this research.

2.6 Summary

This chapter focused on reviewing three related theories: KM, Lean thinking, and Lean-KM. Firstly, the literature review method (i.e. systematic literature review process) adopted in this research was explained. After reviewing and discussing the recent development of the three main theories, four research gaps were identified so as to justify this research and establish a foundation of the conceptual framework. The next chapter will discuss the development of conceptual model and hypotheses.

Chapter 3 Hypothesis Development and Conceptual Model

The previous chapter reviewed the related theories and existing body of knowledge to seek an appropriate conceptual framework and to construct a foundation of hypotheses development. In this chapter, a conceptual model, named Lean-KMPs, is developed based on the literature in the context of manufacturing supply chains. Based on the theories mentioned above, the key components (i.e. four *Lean Wastes*, two *Lean Principles*, and five *Knowledge Management Phases*) and the possible relationships between them are indicated and explained in the first section. Then this chapter includes a conceptual model illustrating the relationships between those constructs. Lastly, hypotheses are proposed concerning relationships between the latent variables in order to test these relationships with empirical data later.

3.1 Latent Variables Development

As already discussed in Chapter 2, Holsapple and Singh (2001)'s knowledge chain model is adopted in this research to represent the whole knowledge management activities. It consists of five dimensions including knowledge acquisition, knowledge selection, knowledge generation, knowledge internalisation, and knowledge externalisation. With regard to the Lean Wastes, after reviewing the previous studies from section 2.3.1 to 2.3.4, the researcher identified four features of wastes that may exist in KMPs of a manufacturing supply chain, which are: 1) excessive information and documentation; 2) failure of information and knowledge demand; 3) inappropriate data and information processing system; and 4) inaccurate data and information. In accordance with these four features, four Lean-KM Wastes have been developed in this research, which includes: 1) *Information Overload*; 2) *Low Quality Information*; 3) *Inappropriate IT System*; 4) *Insufficient Knowledge Inventory*. **Table 3-1** provides a comparison between the classic 7 Lean Wastes in manufacturing systems and the 4 Lean-KM Wastes. For the sake of avoiding repetition in the concepts presented in **Table 2-2**, there is no correspondence for *Waiting, Transport* and *Motion*, since waste from *Waiting* is related to or caused by the 4 Lean-KM Wastes (i.e., time is wasted in searching, locating, correcting, or re-inventing necessary knowledge). In addition, the concept of improving the effectiveness of knowledge flow (i.e., *Transport* & *Motion*) is merged with Lean-KM Principles which is discussed later in this section. Moreover, the reason why *Inappropriate IT System* is corresponding to *Inappropriate Processing* is because nowadays most transactional data, technological processes, and documents are managed and processed by IT system. Hence, Ill-designed IT system could have a negative impact on the knowledge management performance of a company, which also corresponds to the concepts of *Unnecessary Processing* and *Overproduction* in **Table 2-2**. Furthermore, the concept of *Inventory* in the classic seven wastes has been evolved into *Over & Under Stock* presented in **Table 2-2**, it is further divided into two categories in this research: *Information Overload* and *Insufficient Knowledge* Inventory, in order to make the concept of Lean-KMPs more concise and precise.

Table 3-1: The Classic Seven Wastes in Manufacturing and Four Wastes in Knowledge Management

Manufacturing systems	**Knowledge management**
Overproduction	*Information Overload*
Inappropriate Processing	*Inappropriate IT System*
Defects	*Low Quality Information*
Inventory	*Insufficient Knowledge Inventory*
Waiting	Related to: • Information overload • Insufficient k. inventory • Low quality information • Inappropriate IT system
Transport	N/A
Motion	N/A

Source: The Author (2020)

Inspired by Womack and Jones (1996) and Hicks' (2007) the Lean Principles, this research developed two Lean-KM Principles in the context of manufacturing supply chain, as shown in **Table 3-2**. It can be noticed that the concepts of *Specifying Value* and *Identifying the Value Stream* have been combined into *Identification & Usage of Valuable Information and Knowledge*. Since the knowledge chain model (i.e. KMPs) is a knowledge value stream, the Lean-KMPs model is built upon it, so there is no need to re-identify the value stream. Moreover, the KMP is a spiral of continuous process, if the Lean-KM Wastes and Lean-KM Principles can be integrated into KMPs, it will become a continuous improvement process. Thus, *Continuous Improvement* is not included in the Lean-KM Principles as well for avoiding repetition. Lastly, *Pull* is also not included in the Lean-KM Principles, because pure pull principle is not feasible in supply chain KM. In supply chain operation, information, and knowledge delivery systems (e.g. MRP and ERP systems) are task oriented. They usually would apply mixed information delivery methods (i.e. push and pull). The whole operation processes, each task in the process, and the necessary knowledge for each task is clearly defined in these systems. With the help of such IT systems, task related information and knowledge can be "*pushed*" automatically to users. Users, however, can also access previous business operation records at their own discretion from the system's database (Ajial and Sun, 2004). Therefore, manufacturing practitioners would choose systems which not only allow users to have additional flexibility of pulling content based on their needs, but also push the content to them at a predefined frequency (Sun and Liu, 2001; Guo et al., 2015).

Table 3-2: The Classic Five Lean Principles in Manufacturing and Two Lean-KM Principles

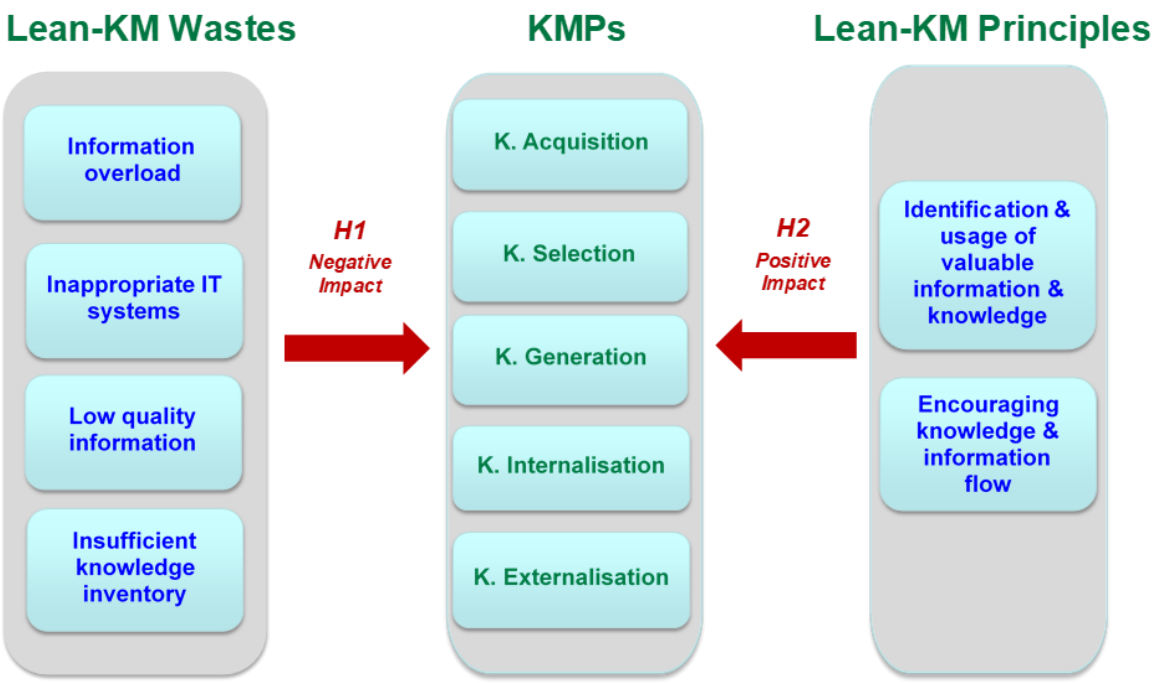
Manufacturing systems	**Knowledge management**
Specifying Value	*Identification & Usage of Valuable Information and Knowledge*
Identifying the Value Stream	
Making Flow	*Encouraging Information and Knowledge Flow*

Pull	N/A
Continuous Improvement	N/A

3.2 Conceptual Model and Hypotheses Development

The aim of this study is to investigate the possible relationships between the three variables: KMPs, Lean-KM Wastes and Lean-KM Principles in the manufacturing supply chain context. **Figure 3-1** depicts the conceptual research model of Lean-KMPs in this study. This model contains two main hypotheses, which are: H1: Lean-KM Wastes have negative impacts on KMPs, H2: Lean-KM Principles have positive impact on KMPs. Each hypothesis is comprised of several sub-hypotheses which will be discussed in the following in detail.

Figure 3-1: Lean-KMPs



3.2.1 The Relationships between Four Lean-KM Wastes and KMPs, and Hypotheses Development

In this section, the four Lean-KM Wastes and related hypotheses in the Lean-KMPs model are justified and explained in detail.

Information overload

Knowledge is the ability of the companies in a supply chain to remember the ways of dealing with complex situations. It can be regarded as experience that is accumulated while running businesses supply chains, or strategic information collected for making effective strategies and solving problems for a supply chain's operation in the future. Today even with the help of advanced IT system in information gathering, sorting, analysis and evaluation, human are still playing an important role in managing and using information (Sadler, 2007). It is a complex interplay between operations, the generation of information and the analysis of information that guides physical action. Too much information can be as much of a burden as too little (Sadler, 2007). Too much information could cause information overload. Because human's information absorbing and processing ability (the quantity of information one can uses for making decision or solving problem within a certain period of time) is limited (Eppler and Mengis, 2004; Stanton and Paolo, 2011). Information overload can be defined as the point where there is too much information it can no longer be used effectively (Feather, 1998). It occurs when the volume of information needed for completing a task exceeds the receiver's information processing capacity (Galbraith, 1974; Tushman and Nadler, 1978). Roetzel (2019, p.484) provided a more detailed definition from a decision making point of view: "*Information overload is a state in which a decision maker faces a set of information (i.e. an information load with informational characteristics such as an amount, a complexity, and a level of redundancy, contradiction and inconsistency) comprising the accumulation of individual informational cues of differing size and complexity that inhibit the decision maker's ability to optimally determine the best possible decision. The probability of achieving the best possible decision is defined as decision making performance. The suboptimal use of information is caused by the limitation of scarce individual resources. A scarce* *resource can be limited individual characteristics (such as serial processing ability, limited short-term memory) or limited task-related equipment (e.g. time to make a decision, budget).* Researchers in various disciplines have found that the quality of decisions is positively correlated to the amount of information an individual is exposed to up to a certain point (a maximum threshold). After this point, the quality of decision making will rapidly decline with the addition of more information (Chewning and Harrell, 1990; Eppler and Mengis, 2004; Karr-Wisniewski and Lu, 2010). Information overload affects decision making in two ways: First, the affected decision maker may be unable to locate the most critical information or knowledge due to sheer volume. Second, information overload may cause decision makers to fail to use the relevant information at hand leading to the inefficient use of decision-making time (Farhoomand and Drury, 2002). In a supply chain, there are three types of information flow (i.e. *internal information flow*, *supplier information flow* and *market information flow*), if any of them are poorly managed it could cause information overload (Jacoby, 1984; Meyer, 1998; Tseng, 2009; Bondarenko et al., 2010).

Internal Legacy Information Overload

In a company, most of the business information is stored in the form of paper or digital documents in the company's database. Keeping and maintaining an ever-increasing archive of legacy information (e.g. out of date transactional and regulatory information), could affect the performance of the user (time wasting) in retrieving critical information (Hicks, 2007). Internal information overload may happen in two circumstances: 1) duplication of documents and confusion as to what the latest version is. The widespread use of shared folders or databases inevitably leads to significant duplication of documents across the organisation, with the same documents being stored many times, by different people in different folders. This means that it can become difficult to tell if an existing copy of a document is the latest or final version leading to confusion as to where the 'single version of the truth' lies and who the owner of the document is; 2) redundant documents (out of date information). It is not practical to store expired data in working databases. As a result, the volume of documents can become unnecessarily large (increasing storage costs and making finding documents more difficult) as many documents are retained that are no longer used and that should really be archived or deleted (Zantout and Marir, 1999; Bondarenko et al., 2010). The result of these situations is that people often access and read the wrong version or copy of a document, make decisions based on the wrong information and potentially release the wrong information which could have damaging effects in terms of costs and company reputation (Bondarenko et al., 2010). Therefore, internal legacy information overload has negative impact on knowledge selection and knowledge generation.

Supplier Information Overload

Many studies conducted on the relationship between consumer decision making and information overload indicated that consumers are often faced with large amounts of complex information; if they attempt to process too much information in a limited time, they may suffer confusion, cognitive strain, and other dysfunctional consequences (Jacoby, 1984; Malhotra, 1984; Chen et al., 2009; Kurt et al., 2011). This situation is similar to supplier selection in supply chain management. Due to rapidly changing and fiercely competitive global markets, supply chain managers must select suitable suppliers quickly to catch the opportunity (Bolukbas and Guneri, 2018). They may face many supplier alternatives, and each alternative has many elements that need to be considered, such as previous experience from doing business with the supplier, price, product quality and features, production and delivery capability, financial stability, technical support availability and willingness to participate as a long-term business partner, inter alia. Therefore, it could easily cause information overload for making the selection decision. Thus, supplier information overload could negatively affect knowledge selection and knowledge generation.

Market Information Overload

Gathering and analysing too much market information regarding competitors, customers, distribution intermediaries, sales personnel, and market trends. could also cause information overload (Meyer, 1998). Today, companies can rely on the help of IT system to collect complex information, but still, they need to be interpreted and analysed by the human brain. Thus, when the amount of data is too overwhelming and there is no systematic method to select and analyse critical information for decision makers, making a strategic trade-off marketing decision would be a challenging task (Tseng, 2009). Therefore, too much information could negatively influence a supply chain manager's ability to select critical information and thus reduce the decision quality. It can be concluded that market information overload could negatively affect knowledge selection and knowledge generation.

Therefore, this study develops the following hypotheses:

Hypothesis 1a: Information overload has a negative impact on knowledge selection.

Hypothesis 1b: Information overload has a negative impact on knowledge generation.

Inappropriate IT System

A supply chain relies on the overall and long-term gain of all members of the chain through cooperation, coordination, and information sharing. This signifies the importance of communication and the application of information systems in supply chain management (Soroor et al., 2009). It is impossible to achieve an effective supply chain without support from a well-designed information technology (IT) system. In the past two decades, enterprise resource planning (ERP) systems have become the most important development in enterprises' use of IT systems (Ruivo et al., 2012). It is a functional extension of the material requirements planning (MRP) systems of the 1970s and of the manufacturing resource planning (MRP II) systems of the 1980s. Instead of concentrating on a few specific functional areas of a single company, like MRP, ERP's main purpose is to integrate all aspects of a business, such as order processing, production planning, purchasing, manufacturing, sales, distribution, financial management, and customer management, and so on, so as to support the strategy, operations and decision making functions in a supply chain. The data and information generated from above aspects is stored, processed, and delivered in real-time to the relevant members including suppliers, managers, staff, and customers. Today, ERP systems have been widely used in both large companies and SMEs. Although ERP systems can help information flow seamlessly across diverse business functions, business units and geographic boundaries, however, using a badly developed one may in fact damage all these benefits expected to the organisation (Kulikov et al., 2020). Researchers have identified several key factors that may negatively affect the successful implementation of ERP system, which include *incompatibility*, *lack of extended enterprise functionality*, *inflexibility*, as well as *culture and content mismatch* (Hanafizadeh and Dadbin, 2010; Amid et al., 2012; Malaurent and Avison, 2015; Saade and Nijher, 2016).

Incompatibility

When a company implements a new ERP system, it is likely that some legacy systems will be retained and must be integrated with the new ERP system. The major difficulties of ERP implementations are the costly development of additional software to help retrieve information from legacy systems (Akkermans et al., 2003; Yusuf et al., 2004; Saade and Nijher, 2016). If the new ERP system cannot read the data or information stored in the old system, engineers have to re-programme the old data format in order to suit the new system, which is expensive and time consuming (Bradford and Florin, 2003; Yusuf et al., 2004; Saini et al., 2013). If such data conversion processes are unsuccessful, it will cause operational and transaction information to be inconsistent, distorted or even lost, which will bring negative effects on an organisation's knowledge sharing and repository function (Law and Ngai, 2007; Choi et al., 2013). Therefore, incompatibility has negative impact on knowledge internalisation.

Lack of Extended Enterprise Functionality

Today's business is moving towards inter-organisational supply chains. Therefore, companies must establish strong partnerships and effective communication with each other (Akkermans et al., 2003). Therefore, supply chain-oriented IT system should be able to facilitates and expedites the exchange of data and information residing in the systems of supply chain partners (i.e. suppliers, customers and channel partners) in real time (Tarn et al., 2002; Goutsos and Karacapilidis, 2004). However, many ERP systems are only design to manage the information and goods flow within a single company under central control. They cannot exchange information in real-time between trading partners' IT systems (Akkermans et al., 2003; Saade and Hijher, 2016). Therefore, without extended enterprise functionality (i.e. data and information can be transferred between supply chain members in real-time), companies in a supply chain cannot make comprehensive operational decisions for their cooperation (Tarn et al., 2002; Soroor et al., 2009; Shatat and Udin, 2012). Hence, lack of extended enterprise functionality could negatively affect knowledge acquisition and knowledge generation.

Inflexibility

Today, customer demands are changing more and more rapidly and frequently. Therefore, business processes and supply chain structures have to adapt ever more quickly in response, and ERP systems should be flexible to this situation. For instance, a single company may have different types of relationships with its suppliers and customers. Some suppliers many have adopted VMI (vendor managed inventory), some may have adopted CPFR (Collaborative planning forecasting and replenishment) or Just-In-Time, and other may still keep in a classical vendor/buyer relation. If the ERP system cannot accommodate all these different modes of collaboration at the same time and change efficiently from one mode to another, members of a supply chain would not be able to make appropriate operational decision or strategy for collaboration with each other (Akkermans et al., 2003). In addition to the inflexibility in adapting to different modes of collaboration, some ERP systems also lack flexibility in business processes reengineering. Many companies have gained benefits from implementation of ERP system by adopting a process redesigning approach that is directed by the functionality inherent in an ERP system. Such an approach uses business process templates that replicate best practices in a particular industry (Allen et al., 2002; Al-Mashari and Al-Mudimigh, 2003; Maguire et al., 2010; Moohebat et al., 2011). This is adequate if these "best practices" are really an improvement on the current business practices. However, much researches on ERP implementation and business process reengineering/redesign (BPR) indicates that many ERP systems, especially more mature ERP like SAP, requires a very rigid business structure in order to work successfully (Moohebat et al., 2011; Zach and Munkyold, 2012; Saade and Hijher, 2016). For example, when Rolls-Royce adopted the SAP system for the first time, the system forced the company to adjust their working practices, or even changed the way they do business (Yusef et al., 2004). In some cases, many suggested business process templates are infeasible or inappropriate for certain companies. As another example, a research project conducted in a Jordanian SME shows that the payment approaches designed into the ERP system for this company is inimical to Jordanian ways of working, which may cause customer loss to this company (Hawari and Heeks, 2010). Therefore, many companies want the system to adapt according to the organisational needs, rather than having to adapt their business processes to the ERP system, because the existing business processes are perceived as a unique source of competitive advantage, and critical for the further functioning of the business (Hawari and Heeks, 2010). If the ERP system is inflexible in BPR, the company would not use it effectively, or even abandon the whole system eventually (Zach and Munkyold, 2012; Saini et al., 2013). This situation could cause negative effects on knowledge acquisition, generation, internalisation, and externalisation as the IT system is the data and information processor and is involved in the most part of KM activities in an organisation.

Culture and content mismatch

Culture issues can influence whether employees are able and willing to use certain technologies (Livermore and Rippa, 2014; Saade and Hijher, 2016). It has been shown by two research projects on ERP implementation in China. They found that language has a significant impact on ERP implementation (Zhang et al., 2003; Liang et al., 2004; Xue et al., 2005). For instance, in some case companies, the selected ERP system package was not fully translated into Chinese. Employees therefore got confused with the English words in the user interface and accounting reports. In addition, the accounting and financing format generated by the ERP system did not the China's accounting standards (Xue et al., 2005; Woo, 2007; Malaurent, J., & Avison, D., 2015). Therefore, the problems mentioned above could cause negative effect on knowledge generation (e.g. accounting statements) and may lead to abandon of the system.

Thus, this study hypothesises:

Hypothesis 1c: Inappropriate information system has a negative impact on knowledge acquisition.

Hypothesis 1d: Inappropriate information system has a negative impact on knowledge generation.

Hypothesis 1e: Inappropriate information system has a negative impact on knowledge internalisation.

Hypothesis 1f: Inappropriate information system has a negative impact on knowledge externalisation.

Low Quality Information

Many researchers have defined quality information but there is no common definition. Lindau and Lumsden (1993) define quality information as correct information which means the right information must be in the right condition and right quantity, and it must be received by the right receiver at the right time and the right place. Closs et al. (1997) and Moberg et al. (2002) developed four dimensions to define quality information, which are timeliness, accuracy, availability and proper formatting to facilitate usage. Li et al. (2005) suggested that information shared among supply chain partners must have timeliness, accuracy, be completed, adequacy and be reliable. By summarising these previous works, Forslund and Jonsson (2007) define and describe quality information with four information quality variables: in time, accurate, convenient to access, and reliable. In time means it is delivered in the agreed time when the information user wants it. Accuracy concerns the degree of completeness and free from obvious mistakes in the information. The information must be complete and corrected before being entered into the company's decision making or planning system. Convenient to access means the ease of using the data without further processing (e.g., adapting an item code or entering it manually into the company's information system). Reliability means that the information will remain unchanged. Unreliable information means uncertainty to the information user, which has to be prevented by using safety mechanisms (e.g., keeping high safety stock and maintaining excessive production capacity). In this research, the authors will adopt the definition provided by Forslund and Jonsson (2007) for the waste of low quality information as follows: the negative effects caused or the effort wasted by using low quality information which is inaccurate, not easy to access, unreliable, and untimely. There are two reasons that cause low quality information or information distortion when data and information are shared among supply chain partners. The first reason is the partner’s attitudes, such as lack of trust and commitment, opportunistic behaviour, too much enthusiasm, inter alia, that change the content of knowledge by adding or subtracting erroneous information (Taylor and Xiao, 2010). The second reason is time-related problems which occur due to lack of information sharing technologies, irregularities and late responses (Sari, 2008; Eksoz et al., 2014).

In a supply chain, sharing and using low quality information could cause serious damage to collaboration and knowledge generation processes among supply chain members. Due to the bidirectional nature of information flow in a supply chain, negative effects could be caused by *low quality information from downstream* and *upstream of a supply chain* (Tseng, 2009; Danese and Kalchschmidt, 2011; Liu et al, 2014a; Cannella et al., 2015).

Low quality downstream information

Downstream information refers to the information acquired from a company’s marketing channels such as wholesalers, distributors or retailers. This type of information includes market trends, consumers’ reactions and feedbacks to the productions or services, product demand information, and demand forecasting information, and so on. (Claro and Claro, 2010). Such information is vital for supply chain integration. Using low quality downstream information would cause serious damage to production, business plans, operation strategy or decisions for a supply chain’s collaborative operations.

From the perspective of a production department, demand forecasting information will be used as a reference for allocating production capacity in advance (e.g., increasing capacity, outsourcing of production in certain periods, or producing products for other companies when demand is low, and so on).

Using inaccurate forecasting information from retailers or wholesalers could cause manufacturing department to make the wrong plan for capacity allocation, which in turn, could lead to poor equipment and labour utilisation (Danese and Kalchschmidt, 2011). In addition, inaccurate information about demand and market trends could also make a company launch less desirable new products. Moreover, many consumers may face common production problems (e.g., customisation, quantity requirements, and poor quality.) and logistics problems (e.g. time, volume, place of delivery, and safety or quality insurance). If the firm could not get timely feedback and opinions from customers, they would not be able to quickly find alternative solutions for these problems (Claro and Claro, 2010).

For sales strategy, salespeople cannot make effective promotion plans for different group of customers if they are using low quality demand and market information (e.g., specific patterns or buying behaviours) (Danese and Kalchschmidt, 2011).

For purchasing plans, purchasing managers make procurement plan for specific material resources by considering how the market will evolve with respect to existing and future products. Therefore, low quality or inaccurate demand and market information could bring negative impact on procurement plans (Danese and Kalchschmidt, 2011).

Furthermore, demand forecasting information is an essential tool for inventory planning. However, it is rarely accurate and becomes even worse at higher levels of the supply chain. In most supply chains, individual members attempt to protect themselves against imaginary shortage (i.e., as opposed to real shortage), and also to get benefits from order batching (Cannella et al., 2015). Therefore, the orders to suppliers will be larger than actual customer demand. This distorted demand information would mislead the upper-level supply chain members to making wrong inventory plans (Lee et al., 2004; Bayraktar et al., 2008; Cannella et al., 2015). Therefore, low quality downstream information has a negative impact on knowledge generation and externalisation.

Low quality upstream information

Upstream information refers to the information acquired from suppliers from upstream of a supply chain. It includes scale and production capacity, delivery ability, product quality, specific technique and public relations (Choy et al., 2007; Tseng, 2009). This type of information is essential for a focal firm (the initiating or governing company in a supply chain) in making decisions about the form of the relationship with its suppliers. The relationship can be either arm's-length or partnership. However, for various reasons, such as lack of effective communication, trusting too much in a supplier's good reputation or lack of prior collaboration experience with a potential supplier, upstream information would be distorted (Pillai and Min, 2010). For example, a potential supplier's skills have been damaged since it has lost personnel recently. Because of having faith in the supplier's good reputation and because of poor communication, the focal firm may not know this situation and still be overconfident about the supplier's capabilities. It may still give a high level of trust and use the supplier as the only source or at least one of few sources rather than searching and developing more suppliers. In the worst scenario, the focal firm might have even made relationship-specific investments. Therefore, if the supplier fails to perform as expected, the focal company would suffer a lot since it has insufficient backup (Day, 2000). Another example, sometimes, the focal firm may doubt about a potential supplier's capability just because they never cooperate with each other before, even if the supplier is ISO 9000 certified. Hence, the focal company would decide to develop an arm's-length relationship with the supplier and look for alternative suppliers for contingency purposes. Therefore, the transaction cost will increase (Pillai and Min, 2010). Therefore, low quality upstream information could bring a negative impact on decision making (i.e., knowledge generation) about partnership or collaboration, as well as productivity (i.e., knowledge externalisation).

Thus, this study hypothesises:

Hypothesis 1g: Low quality information has a negative impact on knowledge generation.

Hypothesis 1h: Low quality information has a negative impact on knowledge externalisation.

Insufficient Knowledge Inventory

The waste of insufficient knowledge inventory includes the resources and activities that are necessary to overcome the lack of information or knowledge. It also means the effort to reinvent wheels or re-discovering knowledge all over again, knowledge and experience that the company has already used but simply allowed to disappear. A company should encourage employees to think, create, and use the thought of all employees, not just managers (Bicheno and Holweg, 2009). This type of waste also refers to knowledge users wasting time in waiting for necessary information and knowledge to make critical decisions. Great business opportunities never last long. An opportunity could easily be lost while decision makers wait for information and knowledge. This type of waste could be caused by poorly managed knowledge acquisition, selection, generation and internalisation (Hicks, 2007; Bicheno and Holweg; 2009).

Knowledge inventory or repository is organisational memory and the capabilities for knowledge users to store and reuse information and knowledge in the future. *"It involves the organisation's routine operations and structures that support employees' quests for optimum intellectual performance and therefore overall business performance"* (Lee and Yang, 2000, p. 786). In the supply chain context, during inter-firm interactions, participants identify, evaluate and capture relevant and valuable perceptions and experiences (knowledge) and then preserve them in the depository of the knowledge network (Li et al., 2011; Liu et al., 2014a). If the organisation has no suitable systems and procedures to track, maintain and update their knowledge the overall knowledge resource will not reach its maximum value (Lee and Yang, 2000). There are three types of knowledge stores in an organisation: *interactional knowledge repository*, *functional knowledge repository,* and *environmental knowledge repository* (Johnson et al., 2004).

Interactional knowledge repository

Interactional knowledge stores consist of knowledge which is used to deal with issues related to interactions with suppliers and customers. Interactional knowledge includes aspects such as communication, negotiation, conflict management, and development and implementation of cooperative programs (Johnson et al., 2004; Liu et al., 2014a). Therefore, it will improve a firm's communication, negotiation, and problem-solving ability for working with their business partners. This type of knowledge is significant in building trust and commitment between supply chain members (Morgan and Hunt, 1994). With sufficient interactional knowledge all parties in a supply chain can efficiently and effectively exchange their thoughts and communicate with each other (Tseng, 2009). From this point, lack of the interactional knowledge repository could have negative effect on a company's knowledge acquisition and generation activities.

Functional knowledge repository

Functional knowledge stores consist of knowledge about how to manage supply chain functions. Functional knowledge is accumulated by companies that work closely with their suppliers in aspects such as cost reduction, quality control, operations and production, logistics and delivery, inventory management, and product development (Johnson et al., 2004). A single company, especially a developing enterprise with little experience, would find it difficult to manage product design, manufacturing and inventory control alone. Hence, if suppliers can participate in programmes such as product development, JIT delivery systems, and total quality management (TQM), it will significantly improve the company's capability in new products or services design and production, and also help them to make a more efficient inventory management strategy (Liu et al., 2014a). Therefore, lack of functional knowledge stores could have negative effects on a company's knowledge externalisation (i.e., production) and generation activities (i.e., product development and operational decision making).

Environmental knowledge repository

Environmental knowledge stores are a firm's knowledgebase about its external operating environment. Environmental knowledge stores include competitive behaviour, market conditions, customers' preference, opinion and behaviours, and variation in laws and regulations (Johnson et al., 2004). Grant (1996) argues that when environmental uncertainty is high, environmental knowledge is the most strategically significant resource of the firm for creating and sustaining a competitive advantage. The following three examples will support his statement. Firstly, companies can adjust their production planning and sales strategy by collecting and analysing the current market response to their products in order to adapt to the ever-changing market. Secondly, by knowing new law and regulations companies make corresponding strategy such as changing their core production and logistics processes. Thirdly, information such as product sales, new customer demands and market trend are very important references for companies to improve their current business plans. Lastly, competitor knowledge, such as competitor's scale and quantity, threat level, manufacturing facilities and methods, R&D abilities, and marketing strategies, inter alia, is significant in an enterprise's strategic planning and product development (Liu et al., 2014a). By gathering and analysing this knowledge a company can understand the current and potential strengths, weaknesses, abilities, and strategies of its competitors, then it can develop the right counterstrategies (Sambasivan et al., 2009; Tseng, 2009). Therefore, lack of the environmental knowledge repository could have negative effects on a company's knowledge externalisation and generation activities.

Thus, this study hypothesises:

Hypothesis 1i: Insufficient knowledge inventory has a negative impact on knowledge acquisition.

Hypothesis 1j: Insufficient knowledge inventory has a negative impact on knowledge generation.

Hypothesis 1k: Insufficient knowledge inventory has a negative impact on knowledge externalisation.

3.2.2 The Relationships between Two Lean-KM Principles and KMPs, and Hypotheses Development

In this section, the four Lean-KM Principles and related hypotheses in the Lean-KMPs model are justified and explained in detail.

Identification and Usage of Valuable Information and Knowledge

The value stream is the set of all the specific actions and processes required to bring a specific product (i.e., goods or service, or a combination of the two) into the hands of the customer. In the knowledge chain context, "*The value stream can be considered to represent the series of processes and activities that ultimately result in the presentation of the information to the information consumer*" (Hicks, 2007, p.244). "*The series of processes*" includes the acquisition, selection, generation, internalisation, and externalisation of information (knowledge), which are the processes of a knowledge chain. Hence a knowledge chain can be regarded as a value stream.

Identifying value and then adding value to the product or service for customers in a value stream is the critical starting point of the Lean Principle. The value can only be defined by the customer's point of view (Sadler, 2007; Hines, 2010). It must be defined in terms of "*a specific product, incorporating goods and service, which meets the customer's needs at a specific price at a specific time"* (Sadler, 2007, p. 217). And "The customer" mentioned here can be any type, including the final customer of a supply chain, the next operational and business process, and the next company along a supply chain.

From the KM perspective, one of the most important functions of KM is to identify and recognise value-adding processes and knowledge resources in order to make sure that every member in the knowledge chain provide specific knowledge resources which meet the knowledge user's requirements in the right form, at the right time and the right cost (Holsapple and Singh, 2001). This is consistent with the Lean Principle. Therefore, the information or knowledge provider should facilitate the acquisition, creation, storage, processing, and supplying of information or knowledge that generates value (other knowledge) for supporting organisations to make sound decisions and strategies so as to achieve all their goals and objectives (Buchanan and Gibb, 1998).

Much literature on valuable information recognises that value is a multidimensional construct and researchers have developed specific attributes as indicators of valuable information. However, until now there is no unified set of attributes or dimensions that exist for defining information value. Taylor (1986) identified five kinds of dimensions that valuable information may possess: accuracy, currency, reliability, validity, and comprehensiveness. Tushman and Nadler (1987) define valuable information as accurate, timely, and concise data. Simpson and Prusak (1995) divided dimensions into five categories: weight (relevance), truth, scarcity, guidance, and accessibility. Gardyn (1997) focused on five attributes of correctness, completeness, consistency, currency, and accessibility. Moberg et al. (2002) stated that valuable information should be accuracy, timeliness, and proper formatting. Li et al. (2005) measured information value by timeliness, accuracy, completeness, adequacy, and reliability. Zhou et al. (2014) measure information flowing in supply chain on nine aspects: accuracy, availability, timeliness, internal connectivity, external connectivity, completeness, relevance, accessibility, and information update frequency. These dimensions mentioned above have many similar attributes. Therefore, by summarising the similar attributes from the previous literatures, and combining the characteristics of information in the supply chain context, this research defines information value from four aspects: *relevancy, timeliness and accuracy, scarcity, and accessibility* (Hicks, 2007, Jonsson and Mattsson, 2013).

Relevancy

Relevancy is the degree to which an information provider can provide useful knowledge to support users in completing their tasks (e.g., making decisions, strategies, and plans). A specific kind of information may be a very significant decision-making factor for one partner or department in the supply chain, but it may be less useful or even meaningless for another. (Lumsden and Mirzabeiki, 2008). For instance, information about placement and sequencing of the products in warehouse and shipment is more useful to the distribution department than to the production department (Lumsden and Mirzabeiki, 2008); Customer forecast and planned order information is more valuable to the company whose demand is fluctuating (that is, varying due to seasonality or other factors) (Forslund and Jonsson, 2007; Jonsson and Mattsson, 2013). Therefore, the information provider needs to understand what the users' task is, how the user can achieve it, and what kind of information resources are required, so as to make sure that the information is task related to the user. The higher the degree of relevancy, the better the decision users can perform, thus the better the task performance that may result (Kuo and Lee, 2009). Moreover, providing task-relevant information could help users to store this information more effectively and also make the retrieval of it from knowledge-base for future usage much easier, because once the information is acquired, users will store it in their knowledgebase based on its character and expected purpose (e.g. establishing a task-relevant catalogue) (Kim et al., 2007; Farris II, 2010). Therefore, task-relevant information would bring positive effects to knowledge generation, selection and internationalisation.

Timeliness and accuracy

Timeliness means information received at the right time, to the right receiver and to the right place (Lindau and Lumsden, 1993). Accuracy means "*freedom from mistake or error; conformity to truth or to a standard or model*" (Michnik and Lo, 2009, p.852). In some situations, without timeliness information cannot reflect the real-time situation accurately.

Most information sharing in a supply chain, such as order quantity, sales volume, product location, delivery time, inventory volume of materials and products, are numeric, they need to be absolute correct, accurate and have zero-defects (Simpson and Prusak, 1995). It has been proved that the inventory volume can be amplified upstream in the supply chain when not sharing accurate demand information with the suppliers (Lee et al., 1997). Thus, timeliness and accuracy are two essential elements of valuable information in demand forecasting, decision and strategy making, and problem solving. Hence, timeliness and accuracy would bring positive effects to Knowledge generation.

Scarcity

Scarcity means *"the value of information which is new or is not freely available to competitor organisations or other potential users*" (Simpson and Prusak, 1995, p.416). It is likely to be at the heart of most efforts to obtain competitive advantage from information and knowledge. In supply chain context, for instance, R&D department gain new technologies from its cooperative partners in order to improve the product design processes and making better products in the market; A professional logistics company provides advance logistics services (e.g., warehouse and distribution management) to its manufacturing partner to improve their logistics performance. These knowledge, expertise, technologies and skills may not be accessible or imitated for other competitors in the manufacturing industry. Therefore, scarcity can positively influence knowledge generation and externalisation.

Accessibility

Accessibility refers to “the availability of information to its potential users when needed and in a form which they can use” (Simpson and Prusak, 1995, p.417). There are two points covered in this definition. Firstly, the necessary information should be easily found and gathered by its likely users. Hence information providers should provide convenient information facilities (e.g. user-friendly software or website) to help the user acquire relevant information and exclude the irrelevant. Secondly, the information provided should be presented in the right format for IT system to further process and be easy to read or be understood by users. Incomprehensible information has no value to users, even it is correct and arrive in time. For example, sales or order information stored on paper printouts or spreadsheets that are not automatically readable by the receiver’s ERP system. In such situations, users have to enter the information manually, which is time consuming and also could result in information registration error (Lindau, 1995). Therefore, information provided to users should be concise, clear and in a uniform format so that users are able to acquire and use it more effectively. To conclude, accessibility could positively influence knowledge acquisition and internalisation.

Thus, this study hypothesises:

Hypothesis 2a: Identification & usage of valuable information and knowledge has a positive impact on knowledge acquisition.

Hypothesis 2b: Identification & usage of valuable information and knowledge has a positive impact on knowledge selection.

Hypothesis 2c: Identification & usage of valuable information and knowledge has a positive impact on knowledge generation.

Hypothesis 2d: Identification & usage of valuable information and knowledge has a positive impact on knowledge internalisation.

Hypothesis 2e: Identification & usage of valuable information and knowledge has a positive impact on knowledge externalisation.

Encouraging Knowledge & Information Flow

The Flow Principle of Lean suggests that the value stream should be made to flow. In the case of supply chain knowledge and information, its aim is to ensure that knowledge flows efficiently and only the most valuable (i.e., relevant, timely and accurate, scarce, and accessible information) knowledge flows (Hicks, 2007). In order to achieve this, there are four elements that have been developed, they are *shared language*, *expanding the communication channel, trustful environment within organisation*, and *trustful relationship with business partners* (Chiu et al., 2006; Du et al., 2012; Alkuraiji et al., 2014; Wah et al., 2018).

Shared language

According to Chiu et al. (2006), shared language can be defined as distinctive terms and vocabulary which members in a community can understand in order to facilitate communication. A shared language incorporates concepts and ideas, which goes beyond the language itself. It deals with "*the acronyms, subtleties, and underlying assumptions that are the staples of day-to-day interactions*" (Lesser and Storck, 2001, P.386). Sometimes certain languages or codes are only used in one department, section or division, for example, jargons, acronyms, legal and technological terms used in the operational department, legal operation section, or R&D department, not understandable to others. This could cause new ideas and innovative point of view to be lost (Bureš, 2003). Nahapiet and Ghoshal (1998) state that a shared language influences the necessary conditions for the sharing and integration of intellectual assets and capital in several ways. Firstly, it helps people to approach others and gain knowledge and information from them. Secondly, shared language provides a common conceptual framework for evaluating the likely benefits of sharing and integration of knowledge. Finally, it also represents an overlap in knowledge. Hence, it can increase the ability of employees and supply chain members to share and integrate the thoughts and ideas they have gathered through social contact and practical experience (Chiu et al., 2006). To conclude, shared language has positive impact on knowledge acquisition and internalisation.

Expanding the communication channels

Expanding the communication channel means creating more communication channels within a supply chain to make the communication among employees and between business partners easier. Due to globalisation, members in a supply chain could be located anywhere in the world. It may result in these companies working in different cultural, legislative, or linguistic environments. Usually, face-to-face communication is the most effective communication method, but the geographical separation makes it hard to fulfil (Nonaka, 1991). Therefore, supply chain partners should create more methods to facilitate their communication, such as using Skype or Zoom web conferencing, or develop online or offline discussion forums regularly, in order to create more chances for employees and business partners to make interaction and share their ideas and insights with each other (Alkuraiji et al., 2014). Imai and Baba (1991) state that intensive interaction between people in networks (a supply chain and a company) makes a continuous flow of new information. As this interaction continues, the process constantly generates information (knowledge) and innovation throughout the organisation constantly. It can be concluded that expanding the communication channels would positively influence knowledge internalisation (flow) and generation.

Trustful environment within organisation

Trust can be defined as belief in the trustworthy intentions of others and confidence in the ability of others (Cook and Wall, 1980). In knowledge sharing, trust could increase overall knowledge exchange, makes knowledge exchanges less costly, and increases the likelihood that knowledge acquired from a provider is sufficiently understood and absorbed for a seeker to use (Abrams et al., 2003). It has been widely demonstrated by many researches as a facilitator for effective information (knowledge) sharing (Renzl, 2008; Hong et al., 2011; Du et al., 2012; Olaisen and Revang, 2017). Trust can be concluded from the following characteristics: enjoying open communication, willingness to take risks to cooperate with partners, not being afraid to share sensitive information (e.g. financial, strategic information and know-how) with partners, believe in the content of the information received, belief in a partner's capability and integrity, and also belief that sharing information can benefit each other (Morgan and Hunt, 1994; Kwon and Suh, 2004).

In the supply chain context, information sharing can occur internally and externally. Internally, knowledge sharing among employees is particularly important in achieving a sustainable competitive advantage (Wah et al., 2018). For example, valuable information can be obtained from production workers or sales representatives who have special insights into the production process or market trends (Cabrera and Cabrera, 2005). This may only happen in a trustworthy atmosphere. When employees feel encouraged and trusted by their managers and peers, are not afraid to lose their unique value by exposing their valuable knowledge and believe that they can achieve mutual benefit, they have high willingness to share their knowledge. Therefore, Trust plays a significant role for people to decide whether or not to cooperate and share knowledge within a company, and hence, trust between employees has positive impacts on knowledge generation and internalisation.

Trustful relationship with business partners

Externally, an integrated supply chain is built upon trust and mutual benefit. For enhancing demand planning, inventory performance, and financial work processes, it requires a high level of trust among supply chain partners to share, for example, confidential and closely guarded financial and strategic information with each other. Without trust and a stable long-term partnership, it cannot be achieved (Du et al., 2012).

The information sharing outcome depends on the quality of the shared information and also the trustful relationships (i.e. the closeness and interaction frequency) between partners involved in the knowledge sharing process (Renzl, 2008; Tamjidyamcholo et al., 2013; Panahifar et al., 2018). In the context of supply chains, the trustful relationship among partners is an importance factor which determines the degree of sharing. Trustful partnership means supply chain partners have a high degree of confidence in each other, have a high degree of agreement with each other on matters of benefit and risk, have a high degree of compatibility in business activities with each other, share similar values with each other, have a high degree of willingness to cooperate in business activities with each other for the long term, and may be able to influence each other's strategic business decisions. It is notable that long-term strategic partners share both strategic and operational information, whereas operational partners share only operational information. Furthermore, the more strategic the partnership, the greater the degree of real-time, dynamic information sharing needed for integrated business operations (Du et al., 2012). Therefore, the more trust the partnership has, the more willing supply chain members will be to share information. In conclusion, trust between supply chain partners has a positive impact on knowledge acquisition.

In addition, trust is an influence on both the provider and receiver of knowledge. If knowledge seekers do not trust the information or knowledge that they receive, they are clearly unlikely to make full use of it as they frequently make personal judgments regarding the value of information by judging the source of the information (Barson et al., 2000; Desouza et al., 2006). In the supply chain context, with enough trust, decision makers would not doubt their trading partner's credibility, reliability and trustworthiness, and they are confident to use the information shared by their partner for decision making (Kwon and Suh, 2004). Hence, trust between supply chain partners has a positive impact on knowledge generation.

Therefore, this study hypothesises:

Hypothesis 2f: Encouraging information and knowledge flow has a positive impact on knowledge acquisition.

Hypothesis 2g: Encouraging information and knowledge flow has a positive impact on knowledge generation.

Hypothesis 2h: Encouraging information and knowledge flow has a positive impact on knowledge internalisation.

3.3 Summary

Based on the literature review in Chapter 2, three latent variables have been developed as the key components of the conceptual framework (i.e. Lean-KMPs) proposed in this chapter, they are: four *Lean-KM Wastes*, two *Lean-KM Principles*, and five *KMPs*. As displayed in Figure 3-1, H1 argued that *Lean-KM Wastes* have negative impacts on *KMPs*, whilst H2 presumed that Lean-KM Principles have positive impacts on KMPs. In addition, each latent variable contains several sub-components. Their possible relations as the research hypotheses have been also explained. The next chapter discusses research methodology.

Chapter 4 Research Methodology

The previous chapter discusses the way in which the integrative conceptual framework has been derived from existing literature. It has also explained the hypotheses development of this research. This chapter discusses the philosophical assumptions, the research approach, the research design, and the strategy of inquiry adopted in this study along with the justifications behind choosing them. Furthermore, since the aim of this study is to examine causal relationships between the latent variables in the Lean-KMPs model, the data collection methods adopted are mainly quantitative, particularly based on partial least squares structural equation modelling (PLS-SEM). Hence, the reasons for adopting PLS-SEM as data analysis method are discussed in this chapter. The chapter ends with a discussion of the research ethics as applied in this research.

4.1 Research Philosophy and Assumption

Any research project is grounded on specific philosophical assumptions which evidence the worldview within which the research is situated, and which can be seen in every step of the research process (Quinlan, 2011). It affects the quality of social science research, so it is viewed as an important notion in research design (Easterby-Smith et al., 2012). Research assumptions and philosophies will underpin the research strategy and methods, because they are considered as the way researchers view the world. This leads researchers to clarify research design (Easterby-Smith et al., 2012; Saunders et al., 2016). However, a researcher's philosophical position and the choice of related research methods can be influenced by practical considerations, such as the time and finances available for their research project, and the data to which the researcher can negotiate access. There is no "the best" philosophy for business and management research as different philosophy suits different aims and different researchers (Saunders et al., 2016).

The research assumptions are "*a framework that guides how research should be conducted, based on people's philosophies and their assumptions about the world and the nature of knowledge*" (Collis and Hussey, 2009, p.55). The philosophical assumptions reflect specific ontologies, epistemologies and axiologies. Ontological assumption refers to the nature and form of the reality that can be discovered, or what can be known In business and management research, it shapes the way in which researcher sees the world of business and management, and therefore helps researcher to decide what to research (Saunders et al., 2016). Epistemological assumption concerns knowing (i.e. what constitutes acceptable, valid and legitimate knowledge, and how people can communicate knowledge to others) (Burrell and Morgan, 1979). With regard to business and management research, since its theoretical base is derived from a mixture of disciplines in the social sciences, natural sciences, applied sciences (e.g. statistics, engineering), humanities and the domain of organizational practice, consequently, different business researchers can use different types of data and information, ranging from numerical data to textual and visual information, to develop new knowledge (Saunders et al., 2016). Axiological assumption refers to the role of values and ethics within the research process. It reflects how the researcher deal with both their own values and those of their research participants. The researcher's values are the guidance for them to make judgments about what kind of research the researcher is conducting and how to go about doing it (Heron, 1996). For instance, in data collection stage of this research, the researcher chooses to use survey questionnaires to collect data, which suggests that generalised law-like views gathered through a large sample size survey are valued more highly than the subjective opinions expressed through several interviews of much smaller sample size respondents. In addition, these research assumptions discussed above can be either objective or subjective. An objective ontological view regards the world and reality as independent and distinctive from the individual, while a subjective ontology argues the existence of a link and dependence between social reality and people (Eriksson and Kovalainen, 2008). Epistemologically, objectivists seek to discover the truth of the social world through observable and measurable facts, while subjectivists tend to adopt different opinions and narratives to help to discover and understand the different social realities of different social actors. Axiologically, since the social entities and social actors exist independently of each other, objectivists seek to keep their research free of values and remain detached from their own values and beliefs throughout the research process in order to avoid bias in their findings. Concersely, subjectivists believe that since they actively use opinions and narratives as data, they cannot detach themselves from their own values. Therefore, they openly acknowledge and actively reflect on and question their own values, and incorporate these within their research (Saunders et al., 2016).

The term research philosophy is concerned with systems of belief, assumptions, and reflexive processes about the development of knowledge in a particular field (Saunders et al., 2016). Five research philosophies were cited by Saunders et al. (2016) as the major philosophies framing business and management research. These are positivism, critical realism, interpretivism, postmodernism and pragmatism (see **Table 4-1**). Generally, positivism is considered as the traditional paradigm of research. Often known as the scientific methods, this approach tends to be objective, and thus more quantitative than qualitative (Creswell, 2009). Interpretivism and postmodernism paradigms are mainly focused on the subjective, qualitative approach, which means that they are based on the participants' views and interpretation of the investigated situation (Creswell, 2009). As for critical realism and pragmatism, the former paradigm can be either quantitative or qualitative, the methods chosen must fit the research subject. The latter one tends to use mixed method (i.e. quantitative and qualitative) to find practical solutions and outcomes (Saunders et al., 2016). **Table 4-1** provides a brief comparison between the five research philosophies in three research assumptions discussed above.

Table 4-1: Comparison of Five Research Philosophies in Business and Management Research

Ontology *(the researcher's view of the nature of reality*	**Epistemology** (*the researcher's view regarding what constitutes*	**Axiology** *(the researcher's view of the role of values in*	**Typical methods**

or being)	*acceptable knowledge)*	*research)*	
Positivism			
Real, external, independent. One true reality (universalism). Granular (things). Ordered.	Scientific method. Observable and measurable facts. Law-like generalisations. Numbers. Causal explanation and prediction as contribution.	Value-free research. Researcher is detached, neutral and independent of what is researched. Researcher maintains objective stance.	Typically deductive, highly structured, large samples, measurement, typically quantitative methods of analysis, but a range of data can be analysed.
Critical realism (Post-positivism)			
Stratified/layered (the empirical, the actual and the real). External, independent. Intransient. Objective structures. Causal mechanisms.	Epistemological relativism. Knowledge historically situated and transient. Facts are social constructions. Historical causal explanation as contribution.	Value-laden research; Researcher acknowledges bias by world views, cultural experience and upbringing. Researcher tries to minimize bias and errors. Researcher is as objective as possible.	Retroductive, in-depth historically situated analysis of pre-existing structures and emerging agency. Methods chosen must fit the subject matter, quantitative or qualitative.
Interpretivism			
Complex, rich; Socially constructed through culture and language. Multiple meanings, interpretations, realities. Flux of processes, experiences, practices.	Theories and concepts too simplistic. Focus on narratives, stories, perceptions and interpretations; New understandings and worldviews as contribution.	Value-bound research. Researchers are part of what is researched, subjective. Researcher interpretations key to contribution; Researcher reflexive.	Typically inductive. Small samples, in-depth investigations, qualitative methods of analysis, but a range of data can be interpreted.
Postmodernism			

Nominal. Complex, rich. Socially constructed through power relations. Some meanings, interpretations, realities are dominated and silenced by others. Flux of processes, experiences, practices.	What counts as “truth” and “knowledge” is decided by dominant ideologies. Focus on absences, silences and oppressed/repressed meaning, interpretations and voices. Exposure of power relations and challenge of dominant views as contribution.	Value-constituted research. Researcher and research embedded in power relations. Some research narratives are repressed and silenced at the expense of others. Researcher radically reflexive.	Typically deconstructive—reading texts and realities against themselves. In-depth investigations of anomalies, silences and absences. Range of data types, typically qualitative methods of analysis.
Pragmatism			
Complex, rich, external. “Reality” is the practical consequences of ideas. Flux of processes, experiences and practices.	Practical meaning of knowledge in specific contexts. “True” theories and knowledge are those that enable successful action. Focus on problems, practices and relevance. Problem solving and informed future practice as contribution.	Value-driven research. Research initiated and sustained by researcher’s doubts and beliefs. Researcher reflexive.	Following research problem and research question. Range of methods: mixed, multiple, qualitative, quantitative, action research. Emphasis on practical solutions and outcomes.

Source: Saunders et al. 2016

The present research adopts a post-positivism or critical realism approach. Positivism supports the application of natural scientific methods to social reality (Bryman and Bell, 2011). Positivists assume that the social world exists externally and believe that investigation of social reality has no impact on that reality, therefore, a social world should be evaluated through objective ways (i.e. research can measure social phenomena) rather than subjective methods such as reflection or intuition (Creswell, 2009; Easterby-Smith et al., 2012). Positivists prefer researching causal relationships by collecting observable data and developing hypotheses based on existing theory (Saunders et al., 2016). Moreover, positivists are likely to adopt a highly structured methodology so as to ease replication (Gill and Johnson, 2010). However, Johnson and Duberley (2000) argue that to understand human behavior and attitudes in a business context, the researcher must consider the people's interpretations and perceptions of reality. Therefore, this research holds a critical realism view, which posits that the reality can only be understood imperfectly and probabilistically as the human factor impedes its full understanding (Howell, 2013). This study considers the impact of four lean wastes and two lean principles on manufacturing industries' knowledge management processes. This reality is seen to be external to the researcher and thus can be observable and objectively measured through companies' knowledge management performance, effective and ineffective knowledge management activities. However, it is also believed that this reality cannot be totally understood in a positivist way because the study is also concerned with the effect of the manufacturing industry practitioners' perceptions, attitudes and opinions toward their company's knowledge management performance. Such an effect comes from the use of Likert scales which are based on respondents' perceptions and views, hence justifying the critical realism ontology. As for the epistemological position, the belief is that the researcher and what is researched are not totally separate as the former had already developed a pre-existing knowledge from the review of literature; however, the objectivity of the investigation can still be pursued with the quantitative measurement of the study's variables. The findings of this research are replicable but can still be fallible because of a different context. In fact, this assumption justifies the use of multi-group analysis for different contexts. Moreover, quantitative approach is usually based on deduction, while qualitative approach is based on induction.

4.2 Research Approach

There are two types of research approaches: inductive and deductive approach. An inductive approach begins with the data and creates a theory from the ground up (Saunders et al., 2016). In other words, the researchers starts from empirical evidence to develop theoretical findings (Eriksson and Kovalainen, 2008). By contrast, with a deductive approach, research starts with theory, often developed from reviewing of the academic literature, then the researcher will design a research strategy to test the theory (i.e. deduction proceeds from theory to empirical investigation) (Collis and Hussey, 2009; Saunders et al., 2016). It involves the use of hypotheses to explain the causal relationships among variables. These variables will be measured by quantitative data which are further analysed by using quantitative methods through numerical comparisons and statistical inferences (Saunders et al., 2016). It is based on the premise that theory is the first source of knowledge, considered as a linear model process (Eriksson and Kovalainen, 2008). Therefore, the inductive approach is dominant in interpretivism for investigating why a phenomenon is happening, whereas the deductive approach is likely to be employed in critical realism to explain what is happening (Saunders et al., 2016). In social sciences, it is agreed that the deductive approach is by far the most popular way to develop the theoretical knowledge base (Eriksson & Kovalainen, 2008).

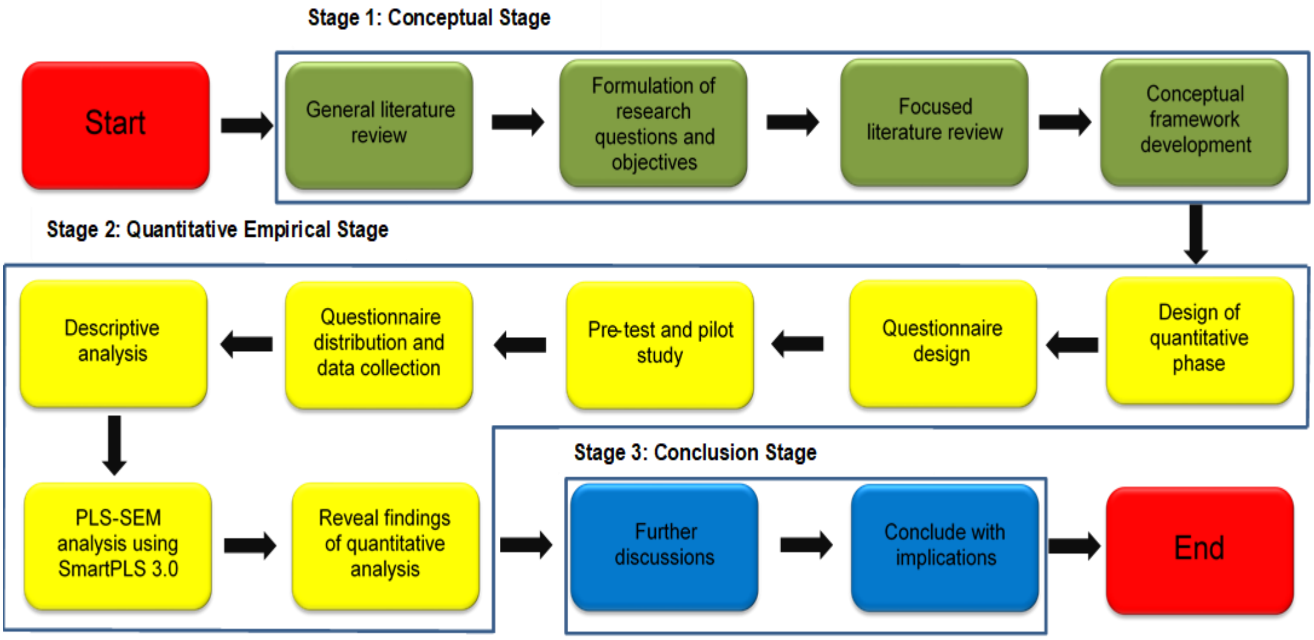
As mentioned in section 4.1, this study considers the impact of Lean thinking on manufacturing industries' knowledge management processes. Its aim is to improve manufacturing companies' knowledge management performance by eliminating the inefficient knowledge management activities and using lean principles as guidance for knowledge management processes. Therefore, a deductive approach was adopted for the present research to test the theoretical model (Lean-KMPs) developed from the pre-existent theories of knowledge chain model and lean thinking. Quantitative methodology is employed because it is concerned with a deductive approach focusing on test theory. Quantitative research is usually about validating theories by investigating relationships between variables, and various instruments can be used to measure these variables (Creswell, 2009). It is basically associated with survey research (Saunders et al., 2016), and closed questions are typically employed in quantitative research using large-scale surveys (Hair et al., 2014). Collis and Hussey (2009) defined survey as a generally critical realistic methodology that investigates a sample of subjects extracted from a population. Such a methodology allows the researcher to draw inferences from the sample studies and generalize them for the targeted population (Gray, 2009). In accordance with the critical realism approach adopted in this study, survey methodology is considered objective, free of bias and impersonal (Kumar, 2008). Surveys attempt to investigate causes and effects occurring between dependent and independent variables under controlled conditions (Gray, 2009). Therefore, the survey method including closed questions is chosen as the major research strategy. In addition, the data collected will be analyzed by using statistical techniques. This type of research generally relates to deductive reasoning. Furthermore, this research will also conduct multi-group analysis by separating the main sample into groups (i.e. countries: China and USA; industries: machinery & electronics manufacturing, and food & drink; company size: small-and-medium and large), in order to compare the differences when the Lean-KMPs model is applied in different context.

4.3 Research Design

The previous sections have discussed the research philosophy and research approach adopted in this project, they influence the way how the research questions will be answered. This section will discuss the research design. Different textbooks place different meaning on research design. Some authors consider research design as the choice between qualitative and quantitative research methods (Creswell, 2009). Others argue that research design refers to the choice of specific methods of data collection and analysis (Easterby-Smith et al., 2012). In this research, a research design is defined as a plan or a framework that contains clear objectives derived from the research questions, development of conceptual framework, and a set of methods and procedures used in collecting and analyzing data, in order to permit a coherent and logical way to investigate the research subject (Saunders et al., 2016).

Figure 4-1 illustrates the research design process of this study. It includes three stages; the end of each stage is the start of the next stage. The green blocks show the research procedures in the conceptual stage (Stage 1), the yellow blocks show the research procedures related to the quantitative empirical phase (Stage 2) and the blue block shows the concluding stage (Stage 3). In Stage 1, a general literature review was carried out to obtain an understanding of the subject being investigated (i.e. knowledge management in the context of manufacturing industry). It also helped the researcher to find research gaps, and frame the research questions and research objectives. After that, a focused literature review was conducted on knowledge chain model and lean thinking in order to define the scope of this research and formulate the conceptual framework. Stage 2 was the quantitative empirical phase. The present study adopted a quantitative method research design based on the critical realism paradigm. Broadly, this approach was employed to test theoretical model developed in the research. It corresponds with the critical realism premise which allows the researcher to stand back, observe and measure the studied phenomenon, and yet still take into account the individual's perceptions and attitudes by using perception-based Likert questions. In this respect, the positivist approach maintains the premise of theory verification which in this case is the Lean-KMPs model. Thus, questionnaire survey was used for collecting data from primary sources, and a pilot test was performed to test the PLS-SEM based online questionnaire which will be explained in more detail in Chapter 5. The data analysis phase included two parts: the first analysis was for the main sample of manufacturing industry practitioner, the second was the comparison of multi-group analysis for different groups, such as countries: China and the USA; industries: machinery & electronics manufacturing, and food & drink; and different company sizes: small and medium, and large, in order to investigate whether there are any significant differences when the Lean-KMPs model is applied in these groups. According to Eriksson and Kovalainen (2008), using a quantitative research design is the most suitable approach that would provide generalisable findings across different contexts. The final stage (Stage 3) discusses the findings by comparing empirical findings with the existing research efforts in the context of manufacturing industry's knowledge management. It provides theoretical contributions and operation management implications along with further research areas.

Figure 4-1: Three Stages of Research Design



Source: The Author (2020)

4.4 Survey Method

Surveys are regarded as a good method for collecting data to measure a number of peoples' opinion and behaviour (Easterby-Smith et al., 2012). According to Cooper and Schindler (2011), there are several methods exist for collecting survey data in a critical realist study, including a structured interview survey by telephone; face to face interview; a structured questionnaire by email, postal mail, fax, or the Internet; and a combination of these. As a researcher, it is very important to be aware of the characteristics of different data collection methods in order to overcome problems such as common method biases (i.e. Common method bias (CMB) happens when variations in responses are caused by the instrument rather than the actual predispositions of the respondents that the instrument attempts to uncover. In other words, the instrument introduces a bias. Consequently, the results the researcher get is contaminated by the 'noise' stemming from the biased instruments) and low response rate (McDonald and Adam, 2003).

A considerable growth in the number of surveys online has been detected for the last decade (Bryman and Bell, 2011). Collis and Hussey (2009, p.191) stated that "*a questionnaire is a list of structured questions, which have been chosen after considerable testing with a view to eliciting reliable responses from a particular group of people*". For this study, the researcher employed a highly structured online questionnaire survey using Qualtrics Software as the main method for data collection. The use of telephone and mail survey was considered but abandoned eventually due to the length of the questionnaire and the wide geographical coverage for delivery and recovery, which may increase the risk of the respondent or interviewer bias, less credibility, and the respondent may stop the conversation at any time (Saunders et al., 2016). It is worth mentioning that the researcher is based in the UK, so posting a large number of questionnaires to the USA and China could have been costly and time consuming. Hence, the use of online questionnaire was considered to be particularly relevant. Furthermore, additional reasons for choosing Qualtrics online questionnaires over other types of questionnaires are that they can be easily accessed by respondents through their computers and smart phones, which means that questionnaires can be delivered faster and relatively cheaper, and also they are more flexible for respondents to answer. The hyperlink of the online questionnaire was texted or emailed to selected respondents, allowing them to complete the survey at their own time. It is the easiest and most effective way to contact extremely busy manufacturing practitioners from different industries and professional roles (Saunders et al., 2016). In addition, since the datasets collected in online questionnaires do not need to be entered manually, they can be analyzed quickly and accurately by researchers. Lastly, with an online questionnaire researcher can pre-screen participants and allow only those who match certain target profile to complete the survey.

However, low response rate is the disadvantage of using online questionnaire. According to Easterby-Smoith et al. (2012), it is common that a twenty per cent response rate can be considered as good, since there is no encouragement for anonymous respondents to demand their cooperation. Another reason for low response rate is "respondent fatigue", it means that if a researcher asked too many questions in a questionnaire, respondents would feel bored and thereby abandon the rest of the questions. Moreover, there is a possibility that people decide to quit answering a questionnaire if they feel bored or it is irrelevant to them (Bryman and Bell, 2011). Yet despite these disadvantages, there are several ways to improve the questionnaires' response rates. First, sending a good cover letter stating the reasons, the motivations and implications of the study and including a target return date can increase the response rates (Bryman and Bell, 2011). A researcher can also assure the respondents of full anonymity and confidentiality in the cover letter (Saunders et al., 2016). Second, response rates can be boosted by an attractive layout and clear instructions (Bryman and Bell, 2011). Third, closed questions and short questionnaires can increase response rate (Collies and Hussey, 2009). Fourth, some methods such as sending follow-up emails and calls can increase the response rates (Sekaran and Bougie, 2009; Zikmund et al., 2013).

In this research, the questionnaire survey explored the effects of lean thinking on manufacturing companies' knowledge management performance. This allowed the researcher to first distinguish the major activities or components included in knowledge management processes, lean wastes and lean principles, and hence to answer the first three research questions of the study. Afterwards, the questionnaire survey explored the effects of lean wastes and lean principles on knowledge management processes identified in the first research question. This answered the last three research questions of the study. It is believed that the use of questionnaires is particularly suitable for the purposes mentioned above. The data obtained by using this instrument is useful to explain the relationships between those variables investigated. According to Bryman (2012), structured and self-administered questionnaires allow the researcher to obtain comparable and standardized responses, so that the differences in these responses can be attributed to meaningful variations rather than to differences in the way of asking the questions (which also corresponds to the perspective of the critical realism approach).

4.5 Sampling Design

4.5.1 Sampling Techniques and Target Population

For social survey research, a sample is a selection of individuals or cases from a larger population that is the full set of cases and highlighted in the research question and objectives (Saunders et al., 2016; Hair et al., 2017). In the sampling process, the individuals are specifically selected to represent the whole population. "*A good sample should reflect the similarities and differences found in the population so that it is possible to make inferences from the (small) sample about the (large) population"* (Hair et al., 2017, p.22-23).

The aim of this research is to analyse the effects of Lean Wastes and Lean Principles on the manufacturing companies' knowledge management processes. This implies that the research population is every individual who is working in manufacturing industry. Therefore, in order to ensure the representativeness of the sample, this research strategically chose the top, senior and middle managers from machinery and electronics manufacturing industry, and food and drink industry in the USA and China as the main target population for the empirical research. The reasons for this sampling decision are: firstly, these people have reached manager level in operations, strategy and marketing departments. Thus, comparing with staff in a low position, they are expected to have longer working experience and sufficient knowledge with regard to the issues investigated in this study, so they are more likely to be able to provide accurate answers to the questionnaire. Secondly, the food and drink industry and machinery and electronics manufacturing are two major components of light industry and heavy industry, respectively. Hence, they have good representativeness for manufacturing industries. Lastly, the USA and China are the two biggest manufacturing countries in the world. According to the most recent data reported by UN Conference on Trade and Development (UNCTAD) for 2015, after taking over the first place from the USA in 2014, Chinese manufacturing output was the highest in the world, $2.0 trillion, which was equivalent to 20% of the world manufacturing output. The USA's manufacturing output totalled $1.9 trillion, the second highest in the world, which accounted for 18% of the world manufacturing output. Japan (10%) and Germany (7%) took the third and fourth place respectively. The manufacturing output in other countries was far less than it in China and the USA. (Rhodes, 2018). Therefore, the sample drawn from these two countries can be considered as good representation of the manufacturing industries in the world.

The unit of analysis refers to the major entity that a researcher is investigating in his/her research project. It is determined by the research question. Example of the different types of analysis units that may be used in a research include individual people; groups of people; objects such as photographs, newspapers and books; geographical unit based on parameters such as cities or countries; and social parameters such as births, deaths, divorces (Babbie, 2020). In order to answer the research question 4, 5 and 6 for this research, the data analysis is divided into two sections: aggregated-level path model analysis and multi-group analysis. The former is to explore the effects of Lean Wastes and Lean Principles on knowledge management processes in the manufacturing supply chain context. Therefore, unit of analysis is the individual top, senior and/or middle managers from manufacturing industry as they are representatives of the manufacturing companies. The latter is to identify if there are any significant differences when the Lean-KMPs model is applied in different contexts (i.e., different countries, different types of manufacturing industries, and different company sizes). Thus, the analysis unit for multi-group analysis is the groups of manufacturing managers with abovementioned different backgrounds.

With regard to the criteria for dividing different company sizes, a review of literature reveals that various definitions about company sizes can be found (Hick et al., 2006; Putzeist et al., 2011), it is commonly recognised that scholars have not provided universal definitions of small, medium and large size companies. Different enterprise sizes have been classified and defined using different criteria including capital assets, turnover level, and number of employees (Shams-Ur, 2001). It is difficult to have a clear definition not only because the definition constantly changes over time, but also because it varies from country to country, including or excluding different size ranges (Xie et al., 2010). In order to facilitate the implementation of support programmes and events to enhance the development of small and mediums-sized enterprises (SMEs) within the European Union (EU) members, the EU has attempted to provide a universal quantitative definition: small business=less than 50 employee & turnover under €10 million, medium business= less than 250 employees & turnover under €50 million (Storey and Greene, 2010). Since then, this definition remains the most commonly used in the European context by many scholars (Harland et al., 2007; Kakouris and Sfakianaki, 2018; Ropret et al., 2018). However, it is still not widely used worldwide. In the United States and Canada, the definition of an SEM varies by industry. In manufacturing, an SME is defined as having 500 employees or fewer. In China, according to the SME Promotion Law of China, the number of employees in a manufacturing SME can be up to 2000 (Chen et al., 2010). However, many studies conducted in a China context adopted either the EU definition or the USA definition (Xiao, 2011; Parnell et al., 2012; Zhao et al., 2013; Parnell et al., 2015; Lo et al., 2016; Williams et al., 2020). Moreover, roughly around 99% of total manufacturing businesses are SMEs (i.e., less than 500 employees) in the USA and the UK (Shapira et al., 2013; Rhodes, 2019), using the Chinese SME definition as the sampling criterion may lower the response rate in these two countries. In conclusion, “number of employees” appears as the most practical option for dividing different business sizes and conducing multigroup comparisons, and therefore was used for this research. A threshold of 500 employees was selected to represent SMEs. Any company with more than 500 employees can be considered as a large company.

There are two types of sampling techniques: probability sampling and non-probability sampling, which are used for different research contexts. Probability sampling means each case of the target population has an equal probability of being selected for inclusion in the sample. To apply probability sampling techniques, the researcher needs to make a complete list of every member of the population. This list is called sampling frame. Each member in the sample is randomly selected from the sampling frame for inclusion in the study (Quinlan, 2011). For non-probability sampling techniques, the probability of each case being selected from the target population is not known because it is not possible to make a complete list of the target population, as a result, it is not possible to guarantee that each case of the population has an equal chance to be included in the study (Saunders et al., 2016). This type of sampling techniques is suitable for this research context, because it is not possible to know every individual in the target population (i.e., the manufacturing managers) and to produce a sample frame accordingly in order to make sure the sample selection is conducted randomly.

Non-probability sampling provides a range of alterative techniques to select samples, the most of them are subjective judgement-based methods. As Saunders et al. (2016) suggested that the choices of these methods depend on the feasibility and sensibility of collecting data to answer research questions and to address research objectives, along with the researcher's resources and ability to gain access to the target population. For many research projects, a researcher may need to use a combination of different sampling techniques. This research adopted both purposive and snowball sampling. Purposive, also called judgemental sampling technique means that the researchers need to use their judgement to select suitable sample members (Zikmund et al., 2013). The criterion for inclusion in the research is that the participants must be able to answer the research questions to meet the research objectives. The participants are key informants on the topic under investigation (Quinlan, 2011). Snowball sampling means that the researcher makes contact with a small group of participants in the target population, conducts the research with these people, and then asks them to identify or recommend further cases through their contacts. The researcher continues this procedure until the sample is as large as is manageable (Bryman and Bell, 2007; Quinlan, 2011). This method is commonly used when the researcher has limited contacts in the desired population.

For this research, purposive sampling involved the researcher drawing on their experience and knowledge to obtain a representative sample within the experts of the food and drink industry and machinery and electronics manufacturing, in the USA and China. The potential respondent mailing list was compiled from the United States Manufacturer Directory, Manufacturing USA, Direct Industry,

中国产业信息网，中国制造交易网 and China Economic Net. The participants selected through snowball sampling were the researcher's family members, colleagues and friends who are managers working in the two industries in China and the USA. Having completed the questionnaires sent to them, they recommended many new participants through email, text message and social media. These new participants, after taking the survey, also invited more people who have similar characteristics to join in the research.

4.5.2 Response Rate and Sample Size

The data collection processes were conducted from April to October 2018. The hyperlink of the online questionnaire was emailed and texted to 936 target respondents in China, and 672 in the USA. The researcher also sent 118 questionnaires to potential participants in the UK in case of a low response rate in the former two countries. However, the responses from the UK was not be used in multi-group analysis for national comparison since the sample size was too small. A detailed explanation will be discussed in the later part of this section. **Table 4-2** summarises the results of the data collection from the three countries and illustrates the response rate for the survey questionnaire.

Table 4-2: The Results of the Online Survey

	Sent Emails	Bounced Emails	Delivered Emails	Returns	Response Rate (%)
China	936	28	908	521 (**Usable: 182**)	19.4%
USA	672	33	639	363 (**Usable: 139**)	20.6%
UK	110	7	103	53 (**Usable: 38**)	34.5%
Total	1718	68	1650	937 (**Usable: 359**)	20.9%

In China, the response ratio of this survey was 521 (182 usable) out of 908 delivered, which records a response rate of 19.4% (usable/sent emails). In the USA, the response ratio achieved was 363 (139 usable) out of 639 delivered, which records a response rate of 20.6%. In the UK, the response ratio was 53 (38 usable) out of 103 delivered, which records a response rate of 34.5%. In total, the response rate from these three countries was 20.9% which may be considered as relatively low. According to Hair et al. (2014), a low response rate may undermine the statistical ability of the collected data and in turn weaken the reliability of the results. This results in the study not being indicative of the complete or a larger population. However, there is no absolute guideline for an ideal response rate. Bryman and Bell (2007) stated that response rates to survey are declining in many countries since the last century. It implies that more and more people tend to refuse to participate in survey research today. In addition, there are many variables that could affect response rates, including *inter alia* the level of effort spent on improving the number of respondents to the survey, the subject matter of the research, and the type of respondents (Bryman and Bell, 2007). For example, people are living in an increasing digitalised world today, they are receiving more spam emails every day and, unfortunately, spam filters are extremely hard on the words like "questionnaire" or "survey". In fact, according to McNabb (2013), there are two major factors that determine the importance of survey response rates: (1) Research purpose: if the purpose of the research is to project results to a larger population, a higher survey response rate is important for assuring the validity of the survey. If the research study's nature is exploratory, like this study that seek insights about general opinions or attitudes, the representation is not as important and hence lower response rate does not impact the research outcome. (2) Data analysis: generally, a minimum sample size is required to determine significance, and lesser responses hamper the ability to conduct significance testing or even statistical analysis. Unlike covariance-based structural equation model tools, it is widely known that the PLS-SEM can produce robust results with relatively limited sample sizes (Henseler et al., 2009; Reinartz et al., 2009; Hair et al., 2017). It "*has higher levels of statistical power in situations with complex model structures or smaller sample sizes*" (Hair et al., 2017, p.24).

In terms of sample size, however, there is no definitive standard. It can be considered as small (less than 100 samples), medium (between 100 and 200 samples) and large (more than 200 samples) (Hair et al., 2010). In addition, Barclay, Higgins and Thompson (1995) proposed a "10 times rule" which is often-cited and applied as a rough guideline for minimum sample size required to run a PLS-SEM algorithm. It indicates *"the sample size should be equal to the larger of (1) 10 times the largest number of formative indicators used to measure a single construct, or (2) 10 times the largest number of structural paths directed at a particular construct in the structural model*" (Hair et al., 2017, pp.24). Despite the fact that Pallant (2013) suggested that when the sample size is greater than 100, the statistical power should not be an issue, Hair et al. (2011) and Marcoulides and Chin (2013) stressed the fact that researchers should take the background of the model, data characteristics and means of statistical power analyses into consideration when determining the required sample size. Therefore, Hair et al. (2017) suggested a rule of thumb developed by Cohen (1992) as guidance to determine the minimum sample size for ensuring the results have adequate statistical power (see **Table 4-3**).

Table 4-3: Sample Size Recommendation in PLS-SEM

Statistical Power of 80%				
Maximum number of arrows pointing at a construct (number of independent variables)	**5% Significance level**			
	Minimum R^2			
	0.10	**0.25**	**0.50**	**0.75**
2	90	33	14	8
3	103	37	16	9
4	113	41	18	11
5	122	45	20	12
6	130	48	21	13
7	137	51	23	14
8	144	54	24	15
9	150	56	26	16
10	156	59	27	18

Source: Adapted from Hair et al. (2017)

For the present study, based on Cohen's statistical power rule, the maximum number of arrows pointing toward one latent construct (Knowledge Generation) is six, thus the minimum sample size required to achieve a statistical power of 80% with a significance level at 5% and detect an R square with at least 0.25, would be 48 observations. As for the 10 times rule mentioned above, the construct with the largest number of arrows pointing at it in both measurement mode and structural mode is Knowledge Generation (KG). It has 11 formative indicators, and hence the minimum sample size would be 110. Therefore, with a total sample size 359, 182 for China, 139 for the USA, and 38 for the UK, it can be concluded that the sample size from these three countries is sufficient to run a robust PLS-SEM analysis.

By the end of October 2018, all the questionnaires have been received back from the participants. The researcher then immediately checked for completeness, suspicious response patterns, outliers, and data distribution. The details will be illustrated in the Chapter 6: Data Analysis.

4.6 Data Analysis Method

This thesis aims to examine the association between multiple independent and dependent variables involving KMPs, Lean wastes and Lean principles. There are several data analysis methods can support this purpose. For example, ANOVA, t-tests, Interpretive Structural Modelling (ISM), Multi-Attribute Utility Technique (MAUT), and SEM can be applied. Amongst these, due to its advantages of flexibility and powerfulness for analyzing multiple relationships simultaneously, SEM is regarded as a rigorous method and highly recommended as a very effective analytical technique by many academics in management, marketing, and information systems (Aibinu and Al-Lawati, 2010; Tabachnick and Fidell, 2012; Takata, 2016; Hair et al., 2018). Thus, this research employs SEM as the main data analysis method for empirical testing the hypotheses proposed in Chapter 3.

Structural equation modeling (SEM) is a type of statistical model that is developed to explain the relationships among multiple variables. It "*enables the researcher to simultaneously examine a series of interrelated dependence relationships among the measured variables and latent constructs as well as between several latent constructs"* (Hair et al., 2014, pp.546). Other multiple regression analysis methods can only test a complex theoretical model in fragments. A SEM model consists of two types of variables: latent variable and observed or measured variables. A latent variable (also called a latent construct) is a hypothesized and unobserved concept that can be either represented or formed by measurable variables (sometimes referred to as indicators). It is measured indirectly by examining consistency among multiple measured variables which are gathered through various data collection methods such as survey, tests, observational methods, etc. In addition, there are two types of latent variables: exogenous latent variables and endogenous latent variables. Exogenous latent variables are independent variables that affect other latent variables, whilst endogenous latent variables are dependent variables that are either directly or indirectly influenced by other variables within the model (Hair et al., 2017). Furthermore, SEM has two types of models: measurement model and structural model. The former depicts relationships between latent variables and observed variables, whilst the latter describes causal relationships between latent variables (Hair et al., 2017). The reason for distinguishing these two types of models is that SEM takes measurement error and structural error into consideration, because it is necessary to explain why observed variables cannot perfectly measure their latent variables and why independent variables cannot perfectly predict the changes in their related dependent variables. There are many reasons for measurement error, including poorly worded questions on a survey, misunderstanding of the scaling approach, and incorrect application of a statistical method. Using SEM can reduce measurement error to make the measure more accurate, because a single concept (e.g. a latent variable) in the theoretical model is measured by several items, rather than single-item, So they are more likely to represent all the different aspects of the concept (Lowry and Gaskin, 2014). In this respect, *"SEM has become de rigueur in validating instruments and testing between constructs"* (Gefen et al., 2000, pp.6).

There are two main approaches to estimating the relationships in a structural equation model: (1) covariance-based SEM (CB-SEM) analyzed through LISREL and AMOS and (2) variance-based techniques represented mainly by partial least squares SEM (PLS-SEM; also called PLS path modeling) (Henseler et al., 2009), which can be analyzed through SmartPLS and WarpPLS. Both methods differ from a statistical point of view, they are designed for dealing with different situations and for achieving different objectives. Neither of the techniques is generally superior to the other, the strengths of PLS-SEM are CB-SEM's limitations and vice versa (Hair et al., 2017). Since its introduction to applied business research by Wynne W. Chin in the late 1990s, PLS-SEM has undergone rapid progress and is becoming an increasingly visible approach for theory testing in many academic disciplines (Cepeda-Carrion et al., 2019; Hwang et al., 2020), such as accounting (Nitzel et al., 2016), hospitality (Zhang and Huang, 2019), operations management (Sousa and Silveira, 2019), and knowledge management (Kianto et al., 2016; Lee at al., 2017; Cabrilo and Dahms, 2018).

The present research adapted PLS-SEM as the primary data analysis method for several reasons. Firstly, PLS is particularly useful for an explanatory research (i.e. testing hypothesis and maximise the variance explained of a dependent variable in a specified model) (Henseler et al., 2009; Cepeda-Carrion et al., 2019). Its goal is to predict key target constructs or identify key driver constructs (Hair et al., 2017). Lowry and Gaskin (2014) added that since PLS avoids factor indeterminacy, it can then be used for both confirmatory studies (i.e., researcher has a theory or several theories, and the objective is to find out if the theory, specified as hypotheses, is supported by data) and exploratory studies (i.e., it aims to uncover possible relationships between variables, and the researcher does not have any prior assumptions or hypotheses). While "*CB-SEM should be used safely only for confirmatory analysis in which well-established theoretical arguments can be used to overrule competing explanations*" (Lowry and Gaskin, 2014, pp.130). This research is an exploratory research. It attempts to explain the variances of knowledge management processes and identifying the key driver constructs (i.e., lean wastes and lean principles).

The second reason for using PLS is that it works efficiently with small sample size. Many scholars agree that unlike CB-SEM, PLS has the ability to provide robust results and achieve higher statistical power when assessing research models with relatively small samples (Goodhue, Lewis & Thompson, 2012; Lowry and Gaskin, 2014; Hair et al., 2017). Higher statistical power implies that the PLS is more likely to detect the significance of a specific relationships when the latter is indeed significant in the population (Hair et al., 2014). As for this research, given the nature of the targeted population (i.e., practitioners in three types of manufacturing industries from three different countries), the sample included in this investigation for each data group was relatively small.

Thirdly, PLS does not require normally distributed data, PLS can still provide correct estimations when distributions are highly skewed, whereas CB-SEM (which relies primarily on maximum likelihood estimation) requires data normality. Thus, PLS has more flexibility in analyzing theoretical models (Gefen et al., 2000; Lowry and Gaskin, 2014; Hair et al., 2017). In this research, the dataset was non-normally distributed as its kurtosis and skewness value are slightly higher than the critical value for normality distribution, which is discussed in section 6.1.4.

Fourthly, unlike CB-SEM, PLS is able to estimate models with both reflective and formative constructs simultaneously (the notion of reflective and formative constructs will be explained in Chapter 6), and is also effective and robust to handle more complex models (e.g., higher-order constructs with a large number of indicators) (Peng and Lai, 2012; Lowry and Gaskin, 2014; Hair et al., 2017). In this research, given the nature of the issue investigated (i.e., knowledge management performance and behaviours) the study involves a large number of constructs including both reflective and formative variables. Hence, PLS-SEM has more freedom for establishing theoretical model for this research.

Furthermore, there are several PLS-SEM software programs in the market for analyzing complex causal models, such as SmartPLS, R-Package, WarpPLS, PLS-GUI, Minitab, and PLS-Graph etc. In this study, the researcher used the SmartPLS, because, comparing with other software programs, it combines state of the art methods (e.g., PLS-POS, IPMA, complex bootstrapping routines) with an easy to use and intuitive graphical user interface so that it enables researchers to be more focused on their research without spending too much time on learning the software. Therefore, for all these reasons discussed above, PLS-SEM is the most appropriate statistical technique to estimate the proposed theoretical model (Lean-KMPs) of this research.

4.7 Research Ethics

Ethics can be defined as a process of reasoning and the moral principles governing an individual, a group or an organization to do the right thing (Quinlan, 2011). When conducting research, it is also very important to consider several ethical issues that may arise in every aspect of the research process. Saunders et al. (2016) state that research ethics as a guidance help the researcher to adopt an appropriate behaviour regarding the rights of the individuals or groups being studied or affected by the study. It outlines what is and is not permissible to do when undertaking research in order to protect both the researcher and their subjects (Kalof et al., 2008). There are five basic ethical principles commonly suggested by several scholars, which should be followed in all stages of the research, from research design to reporting the findings. These are do no harm, integrity and objectivity, informed consent, and anonymity and confidentiality (Kalof et al., 2008; Bryman and Bell, 2011; Quinlan, 2011; McNabb, 2013; Saunders et al., 2016).

Do no harm is the first basic tenet of research ethics. It means that in designing and carrying out the research, a researcher must endeavour to do no harm to individuals or organisations who have agreed to participate in the research (Quinlan, 2011). Harm may occur in a research in the form of either physical or psychological harm or both, including embarrassment, stress, discomfort, pain or conflict. Hence, in this research by the nature of online questionnaire survey, there is no place for any physical harm involved. In order to avoid or at least to minimise any embarrassment and stress to the lowest level as possible, the researcher did not ask any intrusive questions such as how much money a participant earn. In addition, in the covering letter of the questionnaire all the respondents were informed that they can take as much time as they want to complete their questionnaire within two weeks, and they can freely quit and withdraw their answers at any time during the survey.

The Integrity and objectivity of the researcher ensures the quality of the research. This means the researcher should act openly, be truthful and promote accuracy, and also avoid deception, dishonesty, misrepresentation (data and finding etc) and bias. This is particularly important for critical realistic studies (Saunders et al., 2016). From the design and development of this research project, the researcher has always openly and honestly communicated with everyone involved in the project, including the supervision team, colleagues and the survey participants so that any potential ethical risks were likely to be discovered before they become harmful.

Furthermore, the principle of informed consent is another ethical concern (Bryman and Bell, 2011; Saunders et al., 2016). It means that the potential participants should undertake the survey voluntarily and the researcher should clearly explain the nature of the research, the nature and extent of their participation in the research, and any possible consequences for them that might arise from their participation. Hence in this study, the participation was voluntary, and the purpose, risks and benefits of the survey were clearly highlighted in the email invitations and questionnaires.

Moreover, based on General Data Protection Regulation (EU GDPR), when dealing with data and reporting research findings, the researcher has to protect the privacy of the participants, ensuring their anonymity and respecting their confidentiality (Quinlan, 2011). In this respect, the researcher guaranteed that the data contributed by the participants could only be accessed by the researcher himself and the supervision team. The researcher removed all identifying information about the participants from the research records and reports, so that the participants' identity could not be traceable in any publications. Besides, when describing the sample of the study, the researcher only focused on the participants' characteristics rather than their identity. All these ethical considerations were detailed in the email invitations and the covering letter to reassure the participants. Overall, the premise behind all these ethical principles is the avoidance of uncomfortable feelings for the subjects of the research project (Saunders et al., 2016). This was carefully considered in the present study by providing a clear, explicit and precise covering letter highlighting all the ethical aspects mentioned above (See **Appendix B and C: Questionnaire**). The ethical approval application is attached in **Appendix D: Ethical Approval Form**.

4.8 Summary

Research methodology is the guidance for a research to discover new knowledge in a series of logical processes (Saunders et al., 2016). This chapter has presented the methodological steps followed in this study. Firstly, the chapter outlined the philosophical assumptions underpinning the present research, including ontology, epistemology and axiology. It has been stated that this research adopted critical realism or post-positivist approach. The research examined the effect of Lean Wastes and Lean Principles on manufacturing companies' knowledge management processes. This effect was seen to be external to the researcher, thus it can be observed and measured objectively through a statistical approach. However, it was also believed that the effect of the manufacturing industry practitioners' perception, attitudes and opinions toward their company's knowledge management performance cannot be understood perfectly, hence the author holds a critical realism view. Secondly, concerning the research approach and survey method, the present research adopted explanatory deductive approach and mono method quantitative way through the online-based questionnaire survey. Thirdly, section 4.5 discussed the rationale for the sampling design. This research was conducted in two types of manufacturing industries: the machinery and electronics manufacturing industry, and food and drink industry in the USA, China and the UK. The companies are either SMEs or large size companies. A combination of purposive and snowball sampling techniques was employed for the survey, and the total usable sample size was 359. Fourthly, regarding to data analysis method, this chapter justified the adoption of the PLS-SEM amongst various techniques due to its advantages of flexibility and powerfulness for analysing complex theoretical models. Last but not the least, in order to avoid any ethical issue and conduct the research morally, the researcher has followed the five basic ethical principles (i.e. do no harm, integrity and objectivity, informed consent, and anonymity and confidentiality) in all stages of the research, which were also discussed in this chapter. The next chapter will discuss the processes of data collection adopted in this research in detail.

Chapter 5 Data Collection Procedures

The last chapter has discussed research methodology adopted in this research. This chapter will mainly focus on the explanation of the data collection procedures. It contains four sections which are questionnaire design, population and sampling techniques, survey constraints, and back translation approach for translating the questionnaire.

5.1 Questionnaire Design

5.1.1 Structure of the Survey Questionnaire

Generally, questionnaires can be divided into three categories: unstructured, semi-structured, and structured. The unstructured questionnaire consists of open questions, often known as topic-guided questions, which allow free responses. This type of questionnaire is most suitable for interviews in qualitative studies (Saunders et al., 2016). Semi-structured questionnaires comprise a mixture of closed-ended, open-ended and sometimes partially closed-ended questions. They are suitable for investigative studies. Structured questionnaires consist of questions with predefined answers for quantitative analysis This type of questionnaire was used in this study.

In line with the post-positivistic or critical realistic approach of the study, all the questions were close-ended with a defined set of possible answers (Quinlan, 2011). Such a question makes the data collection much easier and facilitates the coding, tabulation and interpretation of data (Bryman and Bell, 2011). The responses were measured on a Likert scale that consists of a scaling procedure enabling the respondents to express their views and opinions on a scale ranging from low and negative answers to high and positive ones (Hair et al., 2017). It is considered to be the most favoured measuring tool used by quantitative researchers (McNabb, 2013). The use of such a scaling system allows the researcher to evaluate the strength of the responses. In addition, it was argued that studies using Likert scale had greater reliability than studies using the categorical variables (i.e. Yes or No) (Madu, 2003). Quinlan (2011) and Hair et al. (2017) indicated that this type of scale allows the researcher to use powerful statistical tools (such as the PLS-SEM) as these are of an ordinal level. Lastly, Likert scales facilitate the questionnaire design process for the research and are relatively easy for the respondent to answer (Bryman and Bell, 2011). The Likert system can use three, five, seven or ten-point scales. According to a study conducted by Carifio and Perla (2007), which compared the use of 5-points, 7-points and 10-points, they concluded that data from Likert items becomes significantly less accurate when the number of scale points drops below five or above seven and the fewer the choices the more manageable it was for respondents completing their questionnaire. Thus, 5-point Likert scale was used throughout the whole questionnaire.

The questionnaire was divided into four main sections (i.e. part 1: respondent and company profile information, part 2: the non-value adding activities, part 3: the value adding activities, and part 4: the company's knowledge production activities), and each section consisted of several sub sections (see **Table 5-1**). The instructions about how to correctly fill out the questionnaire were placed in each section and they were arranged logically to align with the flow of the questionnaire. All questions in the questionnaire was dedicated to top, senior and middle managers who is working in manufacturing industries since they would usually have a more comprehensive view about their companies and industries than their subordinates.

Table 5-1: The Questionnaire Structure

Sections	Sub-section	Category of respondents	Variables to be measured	Type of questions
Part 1: Respondent & company's profile information	—	Top manager, Senior manager, & Middle manager	—	Close-ended with single and multiple options
Part 2: The non-value adding activities	(IO, IIS, LQI, IKI)	Top manager, Senior manager, & Middle	Second-order independent variables (IO, IIS, LQI, IKI);	Close-ended with 5-point Likert scale questions

		manager	First-order independent variables (SIO, MIO, ILIO, INCOMPA, LEEF, INFLEX, CM, LQDI, LQUI, LIKI, LFKI, LEKI)	
Part 3: The value adding activities	(IUVI, EIKF)	Top manager, Senior manager, & Middle manager	Second-order independent variables (IUVI, EIKF); First-order independent variables (RELEV, T&A, SCAR, ACCES, TEO, TRP, SL, ECC)	Close-ended with 5-point Likert scale questions
Part 4: Company's knowledge production activities	(KA, KS, KG, KI, KE)	Top manager, Senior manager, & Middle manager	Dependent variables (KA, KS, KG, KI, KE)	Close-ended with 5-point Likert scale questions

The questions in the part one was about the respondents and their companies' profile information. These questions allowed the researcher to find out the differences when the conceptual framework (Lean-KMPs) (see **Figure 3-1: Lean-KMPs** in Chapter 2) was applied in different groups (i.e. multi-group analysis). In addition, the warm-up questions were also included at the start of the section in order to catch the attention and interest of the respondents. All the questions were close-ended with either single or multiple options to choose from.

Part two was divided into four sub-sections, namely, information overload (IO), inappropriate information system (IIS), low quality information (LQI) and insufficient knowledge inventory (IKI). These sub-sections included questions with regard to the non-value adding activities (Lean Wastes) that may be existing and causing negative impacts on the knowledge management performance of the respondent's organisation. These questions allowed the researcher to measure the independent variables of the path model developed in Chapter 6. All the questions in this section were close-ended with 5-points Likert scales.

Part three was divided into two subsections, namely, identification & usage of valuable information and knowledge (IUVI) and encouraging information and knowledge flow (EIKF). These sub-sections included questions regarding the value adding activities (Lean Principles) that may be existing and bring positive impacts on the knowledge management performance of the respondent's organisation. The purpose of these questions is to measure the independent variables of the path model presented in Chapter 6. All the questions in this section were close-ended with 5-points Likert scales.

Part four was divided into five subsections, namely, knowledge acquisition (KA), knowledge selection (KS), knowledge generation (KG), knowledge internalisation (KI), and knowledge externalisation (KE). These sub-sections included questions on the knowledge management processes that can be regarded as knowledge management performance of the respondent's organisation. These questions allowed the researcher to measure the dependent variables of the path model illustrated in Chapter 6. All the questions in this section were close-ended with 5-points Likert scales.

In order to keep the length of the questionnaire as short as possible for improving completion rate, on average, the number of options in most of the questions was limited to four, and the length of the questionnaire was over six pages approximately. According to Zikmund et al. (2013), online questionnaire should not be more than six pages, if it does, then an incentive would be needed for encouraging the respondent to complete the questionnaire. For this reason, as an incentive if the respondent requests, a detailed report on the final findings of the research will provide to them, which could be of a great help for the manufacturing industry managers as it can act as guidance for them on how to use Lean thinking to improve their company's knowledge management performance, and eventually benefit their company. The final version of the questionnaire and the cover letter are added in **Appendix B and C**.

5.1.2 Measurement Latent Variables

Having clarified the structure of the questionnaire used in this research, this section is going to discuss the instrument chosen to measure the latent variables investigated in the present research. Latent variables are variables which cannot be measured directly because the concept that is supposed to be measured is complex, abstract, and not directly observable, hence they can only be measured by using other variables that can be observed and measured directly (Hair et al., 2017). All these measurements used in this research have been identified from highly ranked journals, and most of them have been tested in previous studies in the field of knowledge management and supply chain management (see Chapter 2 and 3).

The aim of this research is to analyse the effects of Lean Wastes and Lean Principles on the manufacturing companies' knowledge management processes. This implies that the use of Lean thinking would cause changes in the companies' knowledge management performance. Therefore, the independent latent variables in this research are the Lean Wastes and Lean Principles as they are the variables causing changes, and the dependent variables are the knowledge management processes as these are the variables affected by the independent variables. The questionnaire asked manufacturing industry managers a series of questions which were responded to by using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The following will discuss the items selected to measure the latent variables.

Independent Latent Variables

As mentioned above, there are two groups of independent latent variables in this research: four Lean Wastes (i.e. information overload, inappropriate information system, low quality information, and insufficient knowledge inventory) and two Lean Principles (i.e. identification & usage of valuable information and knowledge, and encouraging information and knowledge flow). They are all latent variables which need to be measured by twenty lower order components (i.e. supplier information overload, lack of extended enterprise function, and Timeliness & Accuracy, etc.) (see **Table 5-2** and **Table 5-3**). The measurements of these lower order variables were a combination of different sets of items used and identified in previous studies in order to cover as many types of inefficient and efficient knowledge management activities as possible in manufacturing industries. The respondents were asked to express their opinions about whether there were such activities existing in their company and to what extent. The items either reflected or formed the twenty lower order components.

Table 5-2: Independent Latent Variables for Lean Wastes

Latent Variables	Items	Source
	Information Overload (IO)	
Supplier information overload (SIO)	When our company need to select suppliers in a short time, we had too much different types of information from potential supplier which are difficult to be evaluated and make a choice	Adapted from: Sadler (2007), Hicks (2007), Malhotra (1984)
	…we gathered too much information from potential suppliers, it greatly increased the workload in decision making	
	…we always feel stressful and exhausted to analyse all these information mentioned above from potential suppliers.	
Market information overload (MIO)	When our company need to select a target market to get into in a short time, we gathered too much different types of market information which are difficult to be analysed and make a choice.	Adapted from: Hicks (2007), Jacoby (1984), Malhotra (1984), Tseng (2009), Klausegger et al. (2007), Eppler & Mengis (2004)
	…we gathered and analysed too much market information, and it confused our judgement.	
	…we always feel stressful and exhausted to analyse all these information mentioned above from a market.	
Internal legacy information overload (ILIO)	We keep an ever-increasing archive of obsolete information in company's database, it takes a great effort to maintain and use it	Adapted from: Klausegger et al. (2007), Karr-Wisniewski & Lu (2010), Hicks (2007).
	It takes long time to find useful information in our database which is stacked with a large amount of obsolete information	
	Our database is messed up by outdated and duplicated documents.	
	Inappropriate Information System (IIS)	
Incompatibility (INCOMPA)	Our new information systems are incompatible with the firm's old IT infrastructure.	Adapted from: Rajan & Baral (2015)
	The data and their format in the old information system do not match the requirement of the new information systems	
	The new information system cannot read and store the data from the old information system automatically.	

Lack of extended enterprise function (LEEF)	Our information systems cannot interconnect with our business partners' information system	Adapted from: Akkermans et al. (2003), Soroor et al. (2009), Shatat & Udin (2012), Goutsos & Karacapilidis (2004), Tarn, Yen & Beaumont (2002)
	We have data inconsistency problems with our business partners	
	Our information systems do not support the real-time sharing of information among our trading partners.	
Inflexibility (INFLEX)	Our information systems are not easy to adapt to changes in processes regarding how we do our work	Adapted from: Akkermans et al. (2003), Zach & Munkvold (2012), Yusuf, Gunasekaran & Abthorpe (2004) Hawari & Heeks (2009)
	Our information systems are not easy to adapt to changes in different collaboration modes with our business partners.	
Cultural misfits (CM)	The language shown in our information systems are not accurately translated	Adapted from: Shatat & Udin (2012), Sheu et al. (2004), Xue et al. (2005)
	The formats of tables and reports generated by our information systems do not meet the local government and business partners' requirement.	
Low Quality information (LQI)		
Low quality downstream information (LQDI)	The data and information we get from the downstream of our supply chain is inaccurate.	Adapted from: Chiu et al. (2006), Li et al. (2005).
	We can't use the downstream data without adapting data code or entering it manually into information management system.	
	The downstream data and information we get is not reliable (e.g. demand forecast information keep changing).	
	The downstream data and information we get is untimely.	
Low quality upstream information (LQUI)	The data and information we get from our suppliers is inaccurate.	Adapted from: Chiu et al. (2006), Li et al. (2005).
	We can't use the data from suppliers without adapting data code or entering it manually into information management system.	
	The data and information we get from suppliers is not reliable (i.e. the information keep changing).	
	The data and information we get from suppliers is untimely.	
Insufficient Knowledge Inventory (IKI)		
Lack of interactional knowledge inventory (LIKI)	Our company have very little knowledge in negotiating with trading partners.	Adapted from: Johnson et al. (2004)
	Our company have very little knowledge in planning and management of partnering activities.	
	Our company have very little knowledge in using computers to network and communicate with partners.	
	Our company have very little knowledge in managing conflict with partners.	
Lack of functional knowledge inventory (LFKI)	Our company have very little knowledge in cost-reduction strategies involving suppliers	Adapted from: Johnson et al. (2004)
	Our company have very little knowledge in working with suppliers to develop products.	

	Our company have very little knowledge in working with suppliers to reduce delivery times	
	Our company have very little knowledge in working with suppliers on quality management.	
Lack of environmental knowledge inventory (LEKI)	Our company have very little knowledge in laws and regulations relevant to business partner relationships.	Adapted from: Johnson et al. (2004)
	Our company have very little knowledge in market conditions affecting buying and selling	
	Our company have very little knowledge in labour conditions in supplier firms	
	Our company have very little knowledge in competitors' purchasing and selling behaviours.	

Table 5-3: Independent Latent Variables for Lean Principles

Latent Variables	Items	Source
Identification & Usage of Valuable Information and Knowledge (IUVI)		
Relevancy (RELEV)	We can always locate, use and share the most relevant information and knowledge in our work.	Adapted from: Lumsden & Mirzabeiki (2008), Forslund & Jonsson (2007), Jonsson & Mattsson (2013), Kuo & Lee (2009), Kim et al. (2007), Farris II (2010).
	We can always locate, use and share task-related information and knowledge for daily operations.	
	We can always locate, use and share the most relevant information and knowledge for decision making, planning, problem solving, and product development, etc.	
Timeliness and accuracy (T&A)	Date and information exchange between our trading partners and us is timely and accurate.	Adapted from: Lindau & Lumsden (1993), Michnik & Lo (2009), Simpson & Prusak (1995), Lee et al. (1997)
	We can always get correct data and information when we need it.	
	Supply and demand information shared among our supply chain members is in an agreed time and error-free.	
Scarcity (SCAR)	We have the knowledge that gives us cutting-edge advantages in competition.	Adapted from: Simpson & Prusak (1995), Hicks (2007), Zhou et al. (2014), Lumsden & Mirzabeiki (2008)
	We have the knowledge that is costly to get for our competitors	
	We have the knowledge that we keen to protect from our competitors.	
Accessibility (ACCES)	The required data and information shared and stored in our supply chain is east to find and use.	Adapted from: Simpson & Prusak (1995), Hicks (2007),
	The required data and information shared and stored in our supply chain is in a right format for information management system to process.	
	The required data and information shared and stored in supply chain is understandable and readable for both information management system and users.	
Encouraging Information and Knowledge Flow (EIKF)		
Trustful environment within organisation (TEO)	I can trust the people I work with to lend me a hand if I need it.	Adapted from: Renzl (2008), Bakker et al. (2006)
	Most of my colleagues can be relied upon to do as they say they will do.	
	I feel quite confident that the firm will always try to treat me fairly.	
	I believe sharing knowledge with my colleagues can achieve mutual benefit rather than losing my power and knowledge advantage.	
Trustful relationship with	We and our trading partners can influence each other's business decisions.	Adapted from: Du et al. (2012)
	We and our trading partners have a mutual	

business partners (TRP)	commitment to continue the partnership.	
	We can our trading partners have a high degree of understanding about protecting exchanged business information	
	We can our trading partners have a high degree of smoothly coordinated business actively.	
	We and our trading partners keep each other informed about events or changes that may affect each other's business.	
Shared language (SL)	We use common terms or jargon to communicate with our business partners and employees.	Adapted from: Chiu et al. (2006)
	We use understandable communication pattern during the discussion.	
	We use understandable narrative forms to post messages or articles.	
Expanding communication channel (ECC)	Except using traditional ways (e.g. email, fax, calls or face-to-face), we also use other modern software or apps (e.g. whatsapp and Skype, WeChat, etc.) to communication with our trading partners and employees.	Adapted from: Nonaka (1991), Imai & Baba (1991)
	We create many opportunities to make sure that communications within and outside of our company are regularly and frequently.	
	Communication channels are open in our supply chain.	

Dependent Latent Variables

In this research, the dependent latent variables are the knowledge management processes which can be considered as a company's knowledge management performance. It can be seen from the conceptual model **(Figure 3-1)** in Chapter 3 that changes in the knowledge management processes are caused directly by the four Lean Wastes and the two Lean Principles. By reviewing the literature, it has revealed that knowledge management performance can be measured by the five knowledge management processes which includes the knowledge acquisition, knowledge selection, knowledge generation, knowledge internalization, and knowledge externalization (Holsapple and Singh, 2011; Hicks, 2007; Liu et al., 2014a) (See **Table 5-4**). In this section of the questionnaire, the respondents were asked to express their opinions and judgement about how good their companies' performance was in the field of the five knowledge management processes. The items either reflected or formed these five latent variables.

Table 5-4: Dependent Latent Variables for Knowledge Management Processes

Latent Variables	Items	Source
Knowledge acquisition (KA)	We can effectively acquire crucial information and knowledge from our business partners.	Adapted from: Holsapple & Singh (2001), Hicks (2007),
	Required data and information can be transferred frequently and timely between our company and	

	trading partners.	Liu et al., (2014a),
	We often acquire critical information and knowledge through external survey or external knowledge-rich companies	
	The data and information we got from outside of our company is understandable and usable.	
Knowledge selection (KS)	We can easily find the most relevant information or documents in our database when we need them.	Adapted from: Holsapple & Singh (2001), Hicks (2007), Liu et al., (2014a),
	We are able to locate and assign employees who have right skills or knowledge to complete specific tasks (decision making, product development, problem solving, etc.).	
	We are able to find suitable person in our company to train other employees.	
Knowledge generation (KG)	Our company are able to make accurate supplier selection decisions within a short time.	Adapted from: Holsapple & Singh (2001), Hicks (2007), Liu et al., (2014a),
	Our company are able to accurately target a market within a short time.	
	The report generated from our information management system is fully understandable and its format can meet government and business partners' requirement.	
	We can adjust our business processes plans (day-to-day operations) without any technical constrain from our information management system.	
	We can adjust our partner-style with different suppliers easily and effectively.	
	We have accurate plans for allocating the short and long-term capacity (good equipment and labour utilization).	
	We are able to adjust our marketing strategies successfully.	
	We have efficient inventory strategies.	
	We have successful strategies for keeping reliable partnerships with our suppliers.	
	We can make effective conflict-solving strategies for working with our business partners.	
	We have effective cost-reduction strategies with suppliers.	
Knowledge internalization (KI)	The data, reports and documents can be transferred and stored smoothly in our company's computers without any technological limit.	Adapted from: Holsapple & Singh (2001), Hicks (2007), Liu et al., (2014a),
	Our database is well organized, every piece of information or documents are indexed based on its character and expected purpose.	
	Information and knowledge are shared openly and frequently among our employees.	
	Peer leaning in our company is effectively and efficiently.	
Knowledge externalization (KE)	We are able to launch competitive products and services in the market.	Adapted from: Holsapple & Singh (2001), Hicks (2007), Liu et al., (2014a),
	We have many successful product co-development experiences with our business partners	
	We are able to work with business partners to reduce delivery times effectively.	
	We have many successful experiences of working with business partners on product quality management.	

5.1.3 Pilot Test

Once the questionnaire design was completed, the next step was to conduct a pilot test. A pilot test can be defined "*as a test of the design of the research project, or a test of the data gathering instruments designed for the research"* (Quinlan, 2011, p.341). It can be regarded as a rehearsal of the main questionnaire survey (Kothari, 2004). Usually, a pilot study is conducted with 5 to 15 respondents who have the similar characteristics to the actual respondents in the research (Quinlan, 2011). It is particularly important for a research based on the self-completion questionnaire, because it helps the researcher to check whether respondents understand all the questions, and if not, the problematic questions can be refined before a large number of questionnaires are handed out to the intended participants (Bryman and Bell, 2011).

The main purpose in pre-testing the questionnaire was to evaluate its content validity. According to Saunders et al. (2016), content validity refers to the extent to which the questions in the questionnaire provides adequate coverage of the investigative questions. Adequate coverage can be made through two ways. One is through a comprehensive literature review. Hence, all latent variables in the theoretical model have been selected and defined through an extensive literature review. In addition, most of the questions or items used in the questionnaire have been piloted and employed by other researchers in the previous studies so that the reliability and validity of the questions can be guaranteed. Another way to achieve "adequate coverage" is to use a panel of individuals to assess whether each question is essential and understandable (Li et al., 2006; Saunders et al., 2016). Therefore, the pilot test of the questionnaire was conducted among 6 manufacturing industry practitioners, the researcher's supervision team, and 8 PhD students in the Business School of Plymouth University whose research interests were on supply chain management, logistics, marketing and knowledge management. The purposes of this procedure were to ensure that (1) the questions were clear and had no grammatical and spelling mistakes, (2) the questions accurately expressed the intended meaning, (3) the covering letter was explicit, brief and had no poorly worded instructions, (4) the questionnaire was not so long that respondents would not or could not complete it. After two weeks' time, all the feedbacks were received. There followed several in-depth discussions with industrial practitioners and academics, after which many aspects were revised and modified. This included: (1) the covering letter was found to be too long and containing redundant information, (2) the questionnaire was found to be too long and some items were thought to be repetitive, (3) there were several terminological issues in some of the questions. These terms were too academic and therefore would make it difficult for respondents to understand these questions.

In order to deal with these issues, the content including the information about Plymouth University, the researcher and confidentiality was moved from the covering letter to the consent form at the end of the questionnaire in order to make the covering letter more precise. In addition, the researcher also reduced some unnecessary questions in the Part 1: respondent's profile information, such as the respondents' education background and their company's role in the supply chain (i.e., supplier, buyer, and logistics provider). Because respondent's education level is not directly relevant to this research, and as a manufacturing company, it usually would play all these three roles or two at least (supplier and buyer) simultaneously in its supply chain. Moreover, in order to shorten the length of the questionnaire, several repetitive items in some reflective latent constructs, including the item "We lost many data and information when we transfer them from the old system" in the Question 4 of Part 2, the item "My colleagues and I always share the most useful information to each other during work" in the Question 1 of Part 3, the item "Required data and information are always available to our supply chain members" in the Question 4 of Part 3, and the item "We speak the same language" in the Question 7 of Part 3, were deleted as these items were highly correlated and interchangeable with other items in their corresponding questions. Lastly, several academic terminologies used in some questions were broken down into detailed explanation with simpler words, such as knowledge generation in the questionnaire was replaced by planning, strategy and decision making, and product design; knowledge internalisation was replaced by knowledge inventory and database, or data and information sharing within the organisation; and knowledge externalisation was replaced by production, by doing so the industrial practitioners could easily understand these questions, accordingly the content validity of the questionnaire was improved. After addressing this feedback, a revised version of the questionnaire was checked again by the researcher’s supervision team.

5.2 Survey Constraints

Time and cost are the two major constraints for conducting this research, they will be discussed next.

5.2.1 Time

The author is a full time PhD researcher and can afford to dedicate enough time to the survey, but conducting a research in two different countries was a time consuming task. Therefore, the researcher ensured the completion of the literature review and methodology chapters within two years of study in order to dedicate the whole third year for the data collection process. At an early stage of the PhD study, the researcher has already made personal contacts with people who were working in the food and drink production industry and machinery and electronics manufacturing industry in the USA and China. This helped to improve the response rate within a reasonable time frame.

5.2.2 Cost

The cost is a decisive factor that researchers must consider when conducting data collection for their research. The cost is often mentioned among the disadvantages of the postal survey and personal interviews (Bryman and Bell, 2011; Rea and Parker, 2012). This kind of cost has been avoided by using online questionnaire survey in this research. Most of the costs caused by the questionnaire translation.

5.3 Translating the Questionnaire

Translating questions for a questionnaire survey should be very careful done in order to make sure that the targeted respondents can decode and answer the questions in the way the researcher intended, since some concepts in one language can have different meaning in another language (Saunders et al., 2016). In this respect, it is extremely important to ensure that the questions have the same meaning to all respondents in both countries. Therefore, to ensure the questionnaire is translated in an appropriate way, many researchers conducting international research often use a method called “back translation” to translate their questionnaires. Back translation is a procedure in which a translator or team of professional translators interpret a questionnaire previously translated into another language back to the original language. Usually, in this process, a translator or translators are used who were not previously involved in the project and who have no prior knowledge of the objectives or its specific context (Chen and Boore, 2010). Despite taking extra time, back translation is an excellent way of avoiding errors later on during the data collection process.

In the present research, the questionnaire had to be translated from English into Chinese. The researcher has followed the back translation process. At first, the questionnaire was sent to a translator in China to translate the English version into a Chinese version, and then when this was completed, the new Chinese version was given to a native speaker translator in the UK to translate it back to English. Once these steps were completed, the researcher who is a fluent speaker in English and native speaker in Chinese compared the two versions and modified the questionnaire accordingly.

5.4 Summary

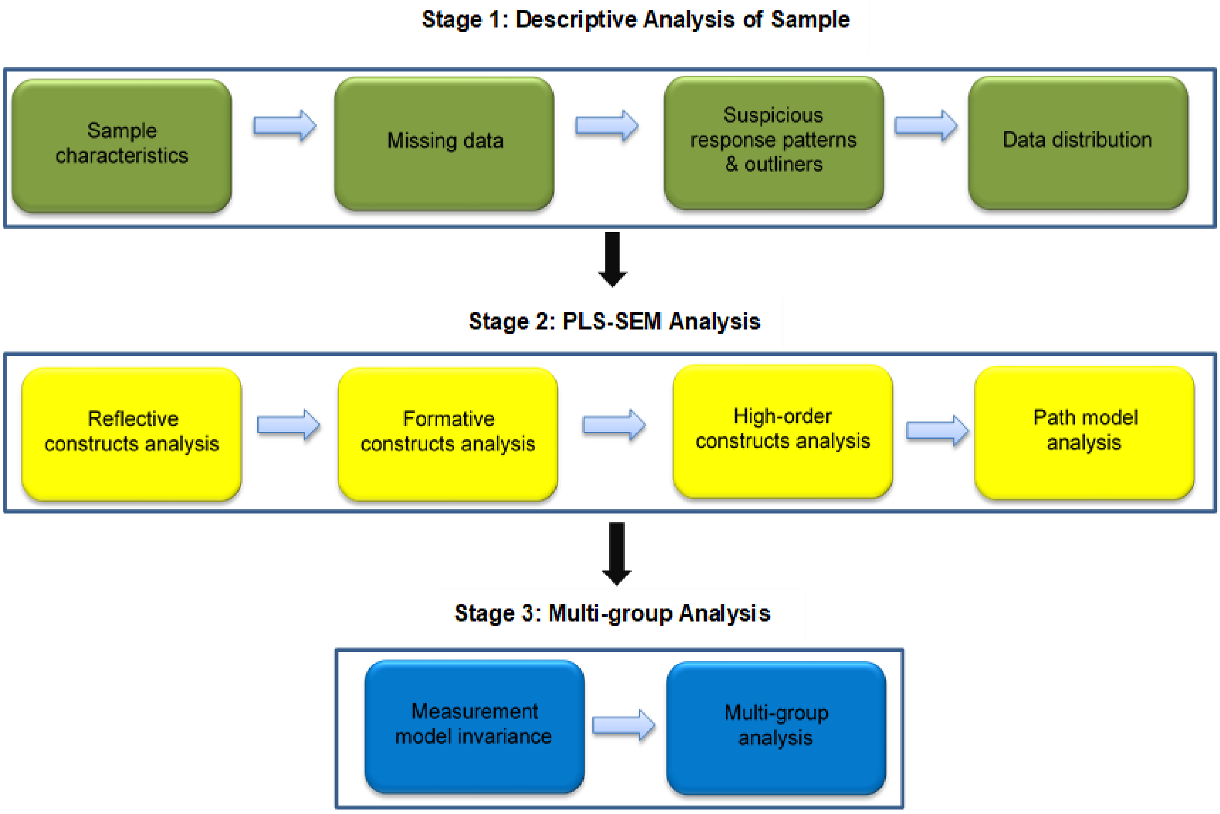
This chapter was devoted to the data collection procedures of this research. At first, the data collection method and questionnaire design were presented in detail. It included how the questionnaire was structured, what measurement items were developed and adopted for identifying the interactions between the different latent variables investigated in the research, and how the questionnaire was piloted before its final launch to the target respondents. Next, survey constraints and the method for translating the questionnaire were also discussed in this chapter. The following chapter will present the results of the quantitative data analysis, which empirically evaluate the Lean-KMPs model and the research hypotheses.

Chapter 6 Data Analysis and Findings

The aim of this chapter is to test the Lean-KMPs model and hypotheses, which were proposed in Chapter 3. Here, the correlation between the Lean thinking (e.g., the four Lean-KM Wastes and the two Lean-KM Principles) and knowledge management processes are evaluated.

Figure 6-1 provides an overview of the data analysis process. Important steps of the process are described in the following sections in detail. Firstly, the chapter begins with the descriptive statistics of the samples, including respondent profile, missing data, outliners, suspicious response patterns and data distribution. Secondly, by using PLS-SEM (SmartPLS 3.0), both measurement and structural models will be evaluated. While the assessment of measurement model reviews how well the variables contained in the theoretical framework are established, the structural model evaluates the relationships between these variables. The measurement model is based on the assessment of the reliabilities and validities of the reflective, formative and high order constructs, whereas the structural model assesses the path coefficients, p values, predictive accuracy (R^2), predictive relevance (Q^2) and effect sizes for confirming or rejecting the hypothesized relationships. Furthermore, the second-order constructs' relative importance and their sub factors' total effects will be evaluated and ranked in order to find out which driver latent variable has the strongest impact on each of the knowledge product processes. In addition, the results obtained in this chapter are based on the data collected from two types of manufacturing industries (i.e., machinery and electronics manufacturing, and food and drink industry), in the two selected countries, namely: China and the USA. Finally, multi-groups analyses are conducted for identifying the differences emerging between these different groups when the Lean-KMPs model is applied to them.

Figure 6-1: Data Analysis Process



Source: The Author (2020)

6.1 Descriptive Analysis of Sample

This section discusses the sample characteristics, missing data, suspicious response patterns, outliners, and data distributions.

6.1.1 Sample Characteristics

This section presents descriptive statistics for the main survey. The profiles of respondents' organisation and their characteristics are summarised in **Table 6-1**. It can be seen that the overall usable sample size is 359. The samples can be categorised in four types of groups: 1) Countries: China (182), the USA (139) and UK (38) accounted for 51%, 39%, and 10%, respectively; 2) Industries: machinery and electronics manufacturing (164) and food and drink industry (195) accounted for 46% and 54% respectively; 3) two company sizes: SMEs (13 + 52 + 63 = 128) and large enterprises (231) accounted for 36% and 64%

respectively; and 4) job positions: top management (28), senior management (86), and middle management (245) accounted for 8%, 24%, and 68%, respectively. Therefore, based on the 10 times rule and Cohen's guidance for the minimum sample size discussed in section 4.5.2, the sample size is sufficient to run both aggregate-level structural model analysis and multi-group analysis robustly.

Table 6-1: The Profile of Respondents

Characteristics	Groups	Overall sample N=359	
		No.	%
Countries	China	182	51%
	USA	139	39%
	UK	38	10%
Industries	Machinery and Electronics Manufacturing	164	46%
	Food and Drink	195	54%
Companies' Size (employee number)	<50	13	4%
	51-250	52	14%
	251-500	63	18%
	>500	231	64%
Job Positions	Top management (i.e. chief executive, owner, director, etc.)	28	8%
	Senior management (i.e. senior manager and departmental manager)	86	24%
	Middle management (i.e. assistant manager, officer, etc.)	245	68%

6.1.2 Missing Data

Missing data occur often in social science research when project data are collected by survey questionnaire (Hair et al., 2017). It is caused by respondents either purposely or inadvertently failing to answer one or more questions, or sometimes, caused by omission during data entering (Hair et al., 2014). If there are only a few missing data in a very large sample, it would not cause serious issues. However, when there is a large number of data missing, it could cause biased parameter estimation and decreased statistical significance (Byrne, 2010; Kline, 2011). Hair et al. (2017) suggested that when there are more than 15% of data missing in a questionnaire, the observation should be removed from the data file. In addition, an entire observation should also be removed from the data file when there is a high proportion of non-response for a single construct, even if the overall missing data on the questionnaire is not beyond 15%.

Smart PLS provides three ways to handled missing data: (1) case-wise deletion; (2) pair-wise deletion; (3) mean value replacement. However, both case-wise deletion and pair-wise deletion have obvious problems. Case-wise deletion means discarding any questionnaire that includes a missing value in any of the indicators and could result in decreasing sample size and biased results. Instead of deleting all observations with missing values, pair-wise deletion uses all observations with complete responses in the calculation of the model parameters. That is, if a respondent has a missing value, the rest valid values are still used to calculate the model. Consequently, it can bias the results since different calculations in the analysis may be based on different sample size. Mean value replacement is to replace the missing value with the mean of valid value of the same indicator. It is easy to apply, but it would decrease the variability in the data and find meaningless results (Arbuckle, 2011; Hair et al., 2017).

Therefore, in order to avoid the negative impacts from missing data, the online questionnaire is adopted as a main survey tool in this research. It is an effective tool for reducing the possibility of missing data. By using it, respondents will be reminded to complete every question before they move to the next one (Hair et al., 2017). Moreover, within the present data set, the researcher has deleted all responses with missing values higher than 15%.

6.1.3 Suspicious Response Patterns and Outliers

Before data analysis, it is necessary to check response patterns for every questionnaire, because suspicious response patterns can yield bias or meaningless results. There are three types of suspicious response patterns: (1) straight lining; (2) alternating extreme pole response; and (3) inconsistent answers. Straight lining occurs in a questionnaire when a respondent selects the same answers for too many questions. Alternating extreme pole response means a respondent marks the questionnaire in a diagonal pattern regularly. Researchers can easily spot these two suspicious patterns by a visual inspection (Hair et al., 2017). In this research, 243 straight lining responses, and 126 diagonal lining and alternating extreme pole responses have been detected and removed from the data set. Inconsistent answers also need to be addressed before analysing the data. It happened very often especially when questionnaires are too long, and respondents lose attention and interest. Misunderstandings about questions could also lead to inconsistent answers. In this research, there are several questions with opposite meaning located in different parts of the questionnaire. In addition, reflective measures are used in the survey, so the same questions are asked with slight variations. If a respondent gives opposite answers to these questions, their questionnaire will be deleted.

Outliers *"are values that are uniquely different from all the other observations and influence results substantially"* (Sarstedt and Mooi, 2014, p. 88). Datasets very often contain outliers. There are three types of outliers. The first type is a result of data collection or entry errors. It has been prevented by online questionnaire since respondents and researcher do not need to enter data manually. Second type of outliers occur because the extreme values are part of reality. Finally, outliners occur when combinations of variable values are extremely rare (Sarstedt and Mooi, 2014; Hair et al., 2017). Once the outliers are detected, the researcher needs to decide whether to retain them. According to the guideline provided by Hair et al. (2017), if there are explanations for exceptionally high or low outliers, they are typically retained, because they represent an element of the population. If the outliers are caused by data entry error, researchers should delete them. If there are no clear explanations, usually outliers can be retained (Sarstedt and Mooi, 2014).

Mahalanobis distance (D^2) is most commonly used for detecting multivariate outliers. Comparing with other methods such as univariate detection and bivariate detection, it can measure more than two variables and researchers do not need to objectively measure the multidimensional position of each observation relative to some common point. According to Hair et al. (2014, p. 64), Mahalanobis measure is a *"multivariate assessment of each observation across a set of variables. It measures each observation's distance in multidimensional space from the mean centre of all observations, providing a single value for each observation no matter how many variables are considered"*. This research used IBM SPSS to examine Mahalanobis distance. **Appendix E** shows that there are three outliers existing according to the extremes value (>=137): response 17, response 95 and response 273 amongst the 359 responses.

All outliers were retained. No outliers were discarded from the dataset because of the following reasons. First, the existence of some outliers within a large sample size should be of minor concern (Kline, 2011). As discussed in section 4.5.2, based on the 10 times rule (the strictest rule), the minimum sample size for this research is 110. 359 responses were collected. Therefore, the sample size is large enough (i.e., >300) to diminish the outliers' impacts. Second, strong proof is required if those outliers are not part of the population (Tabachnick and Fidell, 2012). All the samples selected for this research are the top, senior and managers from machinery and electronics manufacturing industry, and food and drink industry in the USA, the UK, and China. Therefore, every one of them is good representative of the target population (i.e., manufacturing industry practitioners). Third, there is a risk of improving the multivariate analysis but limiting its generalizability, unless outliers are retained (Hair et al., 2014).

6.1.4 Data Distribution

Unlike maximum likelihood-based CB-SEM, PLS-SEM is a nonparametric statistical method, which does not require the data to be distributed normally. However, it is still important to check that the data is not too far from normal because extremely non-normal data may cause problems in the assessment of a parameter's significances (i.e. reduce the likelihood of some relationships between variables) and inflate standard errors obtained from bootstrapping (Hair et al., 2017).

There are two measures to test the data distributions. One is Skewness and the other one is Kurtosis. *Skewness* is used to assess the extent to which a variable's distribution is symmetrical. If the data distribution of responses for a variable is shifted to one side (left or right), then the distribution is skewed. *Kurtosis* is used to assess whether the distribution is too peaked compared with the normal distribution. If the distribution is more peaked than the normal distribution, then it's called *leptokurtic*, while if it is flatter, then it's called *platykurtic*. A general guideline for skewness is that if the number is greater than +1 or lower than -1, it indicates that the data distribution is skewed. This guideline can also be used for checking Kurtosis (Hair et al., 2014).

Table 6-2 presents the distribution of the data set for this research. All the items are ranked based on their absolute skewness and kurtosis value from highest to lowest. Since the list is too long, the table only shows the highest absolute values. The highest absolute skewness value is 1.711 from the item: extended communication channel_1 (ecc_1). And the highest absolute kurtosis value is 3.441 from the item: relevant information and knowledge_1 (relev_1). They have exceeded the critical value for determining substantial non-normality. However, according to Hair (2014), the kurtosis and skewness value can be impacted by the sample size. If the sample size is less than 50 or 30, significant departures from normality can have a substantial impact on the results. If the sample size is more than 200, the impacts may be negligible. Additionally, for sample sizes greater than 300, other studies suggest that the data distribution would not be considered as non-normality unless the absolute skewness value is larger than 2 or 3, or the absolute kurtosis larger than 7 or 10 (Kline, 2010; Kim, 2013). Thus, if the sample size is large enough (i.e. >300), the researcher can be less concerned about non-normal variables. In this research, the sample size is 359, and the data distributions are still within the acceptable range of normality based on the more liberal standard discussed above. Hence, the following data analysis can be carried out.

Table 6-2: The Skewness and Kurtosis Value of the Variables

	No.	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
ecc_1	64	0	4.29	5	1	5	0.97	2.799	-1.711
relev_1	40	0	4.039	4	1	5	0.782	3.441	-1.403
teo_4	55	0	4.318	5	1	5	0.864	1.815	-1.392
teo_1	52	0	4.092	4	1	5	0.79	2.613	-1.255
sl_1	61	0	4.217	4	1	5	0.722	3.12	-1.202
relev_2	41	0	4.106	4	1	5	0.779	2.521	-1.18
kg_1	74	0	3.677	4	1	5	1.13	0.651	-1.154
kg_3	76	0	3.958	4	1	5	1.185	0.467	-1.118
ecc_2	65	0	4.05	4	1	5	0.856	1.761	-1.113
ka_2	68	0	3.772	4	1	5	1.114	0.492	-1.046
teo_2	53	0	4.056	4	1	5	0.784	2.032	-1.037
trp_2	57	0	4.061	4	1	5	0.748	2.029	-1.024
scar_2	47	0	4.025	4	1	5	0.945	0.975	-1.024
ki_3	87	0	3.967	4	1	5	0.873	1.35	-1.02
relev_3	42	0	4.145	4	1	5	0.924	0.671	-0.994

	No.	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
relev_1	40	0	4.039	4	1	5	0.782	3.441	-1.403
sl_1	61	0	4.217	4	1	5	0.722	3.12	-1.202
ecc_1	64	0	4.29	5	1	5	0.97	2.799	-1.711
teo_1	52	0	4.092	4	1	5	0.79	2.613	-1.255
relev_2	41	0	4.106	4	1	5	0.779	2.521	-1.18
scar_3	48	0	4.072	4	1	5	0.765	2.113	-0.986
teo_2	53	0	4.056	4	1	5	0.784	2.032	-1.037
trp_2	57	0	4.061	4	1	5	0.748	2.029	-1.024
teo_4	55	0	4.318	5	1	5	0.864	1.815	-1.392

6.2 PLS-SEM Analysis

Prior to proceeding to the model analysis itself, it is necessary to explain different types of models and constructs employed in PLS-SEM analysis. To begin with, a PLS path model is a diagram used to represent the hypotheses and variable relationships that are assessed when PLS-SEM is applied. This model contains two types of models, one is structural model (also called the inner model), the other one is called measurement model or outer model. The structural model displays the relationships (paths) between the latent constructs (Jarvis et al., 2003), and the measurement model represents the relationships between constructs and their assigned indicators (Hair et al., 2017). A PLS path model is usually analyzed and interpreted in a sequence of two stages: (1) the assessment of the measurement model; (2) the assessment of the structural model (Hair et al., 2017). In order to obtain a sound analysis for research, it is necessary to establish the right description for the measurement models (Jarvis et al., 2003). The measurement model analysis includes the assessment of the reliabilities and validities of the reflective, formative and high order constructs. Without these assessments, the results derived from the structural model analysis would be biased and therefore unreliable (Henseler et al., 2009; Hair et al., 2017).

Latent constructs (i.e. variables that are not directly measured) are the components of a structural model. The indicators, also called items or manifest variables, are the directly measured proxy variables that contain the raw data (Hair et al., 2017). They are the questions in the survey questionnaire. Relationships between constructs and their assigned indicators are shown as singled-headed arrows that can be interpreted as causal relationships. In addition, there are two types of latent constructs: reflective and formative (Mackenzie et al., 2011). According to Hair et al. (2017), the reflective measurement models are commonly used in social sciences and are directly based on classical test theory. In a reflective construct, indicators represent the effects of the reflective latent constructs. Therefore, the causality (i.e. arrow) goes from the construct to its indictors. Since a reflective construct dictates that all indicator items are caused by the same construct, these indicators should be highly correlated with each other, interchangeable, and removing any single item cannot change the meaning of the construct (Hair et al., 2012). In contrast, formative measurement models are assumed to be the causes of their latent variable and are usually uncorrelated with each other. In addition, indicators can be considered as the form factors of a particular construct. Hence, each indicator in a formative construct captures a specific aspect of the construct's content. In other words, the items determine the meaning of the construct, and dropping one of them can potentially alter the nature of the construct.

A latent construct could be a first order, second order, or even a third order construct in a hierarchical component model (HCM). A first order construct can be considered as a single layer construct, second order construct is double-layered construct that contains a number of first order constructs capturing different facets of the construct, and so on. In this research, these higher order constructs are used for the exogenous latent variables. For example, a second order construct is used for the construct *Identification and Usage of Valuable Information and Knowledge* (IUVI), this is represented by four first order constructs capturing various facets including information relevancy, timeliness and accuracy, scarcity, and information accessibility. Higher order constructs are used when the constructs are quite complex and can also be operationalized at higher levels of abstraction. Hence, using second order construct enhances the theoretical parsimony of the study and decreases the model's complexity. Another reason to use HCM is, if the first order constructs are highly correlated, estimations of the structural model relationships may be biased as a result of collinearity issues, and discriminant validity may not be established. Establishing a higher order structure can reduce collinearity issues and may solve discriminant validity problems (Hair et al., 2017). Furthermore, HCM can also solve high levels of collinearity problems in formative indicators, as long as theory supports this step, these indicators can be split and establish separate first order constructs that together form a higher order structure (Chin,1998a; Hair et al.,2017). Moreover, there are four main types of HCMs used in SEM applications: reflective-reflective, formative-reflective, reflective-formative, and formative-formative (Ringle et al., 2012). It means that each HCM type can be characterized by different relationships between the higher order construct (HOC) and the lower order constructs (LOC), and the constructs and their indicators. For example, the reflective-reflective HCM type indicates a reflective relationship between the HOC and the LOC, and all first order constructs are measured by reflective indicators. Conversely, the formative-formative HCM type indicates formative relationships between the LOCs and the HOC, and all first order constructs are measured by formative indicators. The selection of the appropriate type of HCM is based on a priori established theoretical support (Hair et al., 2017). In the path model of this study, the researcher used formative-formative and reflective-formative type constructs to represent four lean wastes (i.e. information overload, inappropriate information system, low quality information, and insufficient knowledge inventory) and two lean principles (i.e. identification and usage of valuable information, and encouraging information and knowledge flow), and first order constructs to depict knowledge management processes (i.e. knowledge acquisition, selection, generation, internalization, and externalization). The high-order constructs analysis will be explained in more detail in the sub-section 6.2.3.

6.2.1 Reflective Constructs Analysis

Assessment of reflective measurement models includes *composite reliability* to evaluate **internal consistency**, *individual indicator reliability*, and *average variance extracted (AVE)* to evaluate **convergent validity**. The assessment also includes **discriminant validity**. The *Fornell-Larcker criterion, cross-loadings*, and especially the *heterotrait-monotrait (HTMT) ratio* of correlations can be used to examine discriminant validity (Hair et al., 2017).

Internal consistency

Cronbach’s alpha is a traditional criterion for evaluating internal consistency. It provides an estimate of the reliability based on the intercorrelations of the observed indicator variables. However, Cronbach’s alpha has some limitations, such as it is sensitive to the number of items in the scale and tends to underestimate the internal consistency reliability. Comparing to Cronbach’s alpha, composite reliability is more appropriate to test internal consistency reliability. Nevertheless, according to Hair et al. (2017), when assessing the internal consistency reliability of a measure, researchers should report both Cronbach’s alpha value and composite reliability value. The former tends to have relatively low reliability values (representing the lower bound), while the later usually results in comparatively higher reliability values (representing the upper bound). Thus, the true reliability usually lies between them (Hair et al., 2017).

In this research, there are 12 reflective measurement models: *1) Supplier Information Overload* (SIO); *2) Market Information Overload* (MIO); *3) Internal Legacy Information Overload* (ILIO); *4) Incompatibility* (INCOMPA); *5) Lack of*

Extended Enterprise Functionality (LEEF); *6) Relevancy* (RELEV); *7) Timeliness and Accuracy* (T&A); *8) Scarcity* (SCAR); *9) Accessibility* (ACCES); *10) Shared Language* (SL); *11) Expanding Communication Channel* (ECC); *12) Knowledge Acquisition* (KA). **Table 6-3** below shows the reflective constructs' composite reliability and Cronbach's alpha value. According to Hair et al. (2017), the composite reliability and Cronbach's alpha vary between 0 and 1. Higher values indicate higher levels of reliability. Values between 0.70 and 0.90 can be regarded as an ideal range. Value range between 0.60 and 0.70 is still acceptable in exploratory research. Values above 0.90 (and definitely above 0.95) are not desirable because they indicate that all the indicator variables are measuring the very same phenomenon by using semantically redundant items. Finally, composite reliability values below 0.60 means a lack of internal consistency reliability. It can be seen from **Table 6-3** that the lowest Cronbach's alpha value is 0.528 from the construct SL. However, its composite reliability value is 0.757 which is above the threshold 0.70. Its true reliability lies between these two values, which is above the threshold 0.60 and in an acceptable range. In addition, the highest composite reliability value is 0.922 from the construct INCOMPA. However, its Cronbach's alpha value is 0.819. Hence, its true reliability is lower than the threshold 0.95. As the result, all the reflective measurement instruments employed in this study have a satisfactory internal consistency reliability.

Table 6-3: Composite Reliability and Cronbach's Alpha

Constructs	Cronbach's Alpha	Composite Reliability
ACCES	0.728	0.846
ECC	0.617	0.785
ILIO	0.812	0.917
INCOMPA	0.819	0.922
KA	0.828	0.918
LEEF	0.792	0.878
MIO	0.867	0.919
RELEV	0.765	0.865
SCAR	0.653	0.81
SIO	0.868	0.919
SL	0.528	0.757
T&A	0.863	0.916

Convergent validity

Convergent validity defined by Hair et al. (2017) is the extent to which a measure correlates positively with alternative measures of the same construct. In order to evaluate convergent validity, researchers should analyse the average variance extracted (AVE) value and the outer loading of the indicators respectively. According to Hair et al. (2017), AVE value should be above 0.50, which means that the latent construct can explain more than 50% of its indicator's variance. Conversely, if an AVE is less than 0.50, it means that more variance remains in the error of the items than in the variance explained by the construct. As shown in **Table 6-4**, all the reflective constructs' AVE values are above 0.5.

Table 6-4: The AVE Values of the Reflective Constructs

Constructs	Average Variance Extracted (AVE)
ACCES	0.647
ECC	0.554
ILIO	0.809
INCOMPA	0.82
KA	0.736
LEEF	0.707
MIO	0.79
RELEV	0.681
SCAR	0.587
SIO	0.792
SL	0.512
T&A	0.785

In addition, based on a common rule of thumb, outer loadings of each indictor should be greater than 0.7. Higher outer loadings on a construct indicate that the associated indicators share more similarities (Hair et al., 2017). As can be seen from **Appendix F**, there are three indicators' outer loading below the threshold 0.7, which are ecc_1 (0.592), sl_1 (0.693), and sl_2 (0.642). However, according to Hair et al. (2017), indicators with outer loading between 0.40 and 0.70 should not automatically be deleted from the scale unless the deletion leads to an increase in the composite reliability (or AVE) above the suggested threshold value. In addition, researchers also need to consider to what extent the deletion of the indicator could affect content validity. If the indicator has a great contribution to the content, then it should be retained. However, indicators with very low outer loadings (e.g., <0.40) should always be eliminated from the construct (Bagozzi, Yi, and Philipps, 1991; Hair et al., 2017). Therefore, these three indictors (e.g., ecc_1, sl_1 and sl_2) will be retained as their outer loadings are not too far from the threshold 0.7 and they have their own special contributions to the content of the associated constructs.

Discriminant validity

The purpose of discriminant validity is to examine the extent to which a construct is truly distinct from other constructs. Hence, establishing discriminant validity means that a construct is unique, and its contents are not captured by other constructs in the model. Traditionally, there are two approaches to assessing the discriminant validity of the indicators. The first one is called cross-loadings. It requires that an indicator's outer loading on the associated construct should be greater than any of its correlations (e.g., cross-loading) on other constructs (Hair et al., 2017). In this research, as can be seen in **Appendix G**, the reflective indictors' outer loadings always exceed their cross-loadings. So, there is no discriminant validity problem. The second approach is called the Fornell-Larcker criterion. It compares the square root of the AVE values with all latent variable correlations (i.e. formative and reflective). Specifically, to establish discriminant validity, the square root of each construct's AVE must be larger than its correlation with other constructs (Hair et al., 2017). From **Appendix H**, it can be seen that there is no discriminant validity problem as all the square root of each reflective construct's AVE are the largest value in their rows and columns.

In recent research, Henseler et al. (2015) argue that the traditional approach (i.e. the cross-loadings and Fornell-Larcker criteria) for discriminant validity assessment have some drawbacks. As a remedy, researchers should also assess the heterotrait-monotrait ratio (HTMT) of the correlations. HTMT is the ratio of the between-trait correlations to the within-trait correlations. It is an estimate of what the true correlation between two constructs would be, if they were perfectly measured (Henseler et al., 2015). According to Hair et al. (2017), the exact threshold level of the HTMT is subjective. Kline (2011) use the more rigorous cut-off of 0.85, while Gold et al. (2001) and Henseler et al. (2015) suggest a threshold level of 0.9. Garson (2016) holds the even more liberal view that if the HTMT value is below 1, discriminant validity has been established between a given pair of reflective constructs. **Table 6-5** shows that the highest HTMT ratio is from *Supplier Information Overload* (SIO) to *Market Information Overload* (MIO) (0.913), which is still below the threshold 1.

Table 6-5: Heterotrait-Monotrait Ratio (HTMT)

	ACCES	ECC	ILIO	INCOMPA	KA	LEEF	MIO	RELEV	SCAR	SIO	SL	T&A
ACCES												
ECC	0.726											
ILIO	0.509	0.483										
INCOMPA	0.518	0.506	0.772									
KA	0.438	0.434	0.713	0.751								
LEEF	0.698	0.602	0.651	0.629	0.253							
MIO	0.328	0.331	0.808	0.778	0.753	0.546						
RELEV	0.639	0.775	0.323	0.374	0.298	0.557	0.206					
SCAR	0.732	0.77	0.366	0.448	0.431	0.605	0.305	0.735				
SIO	0.332	0.385	0.793	0.85	0.805	0.509	0.913	0.184	0.36			
SL	0.558	0.8	0.434	0.501	0.435	0.699	0.375	0.667	0.763	0.365		
T&A	0.687	0.554	0.791	0.774	0.734	0.402	0.761	0.505	0.611	0.785	0.527	

HTMT can also be used as the basis of a statistical discriminant validity test. By using the bootstrapping procedure provided in SmartPLS, the bootstrap confidence interval will be derived. The confidence interval is the range which the true HTMT value will fall into. If a confidence interval includes the value 1, which means that a pair of constructs' discriminant validity is not established. As can be seen from **Table 6-6**, neither of the confidence intervals between 2.5% to 97.5% includes the value 1. Therefore, the discriminant validity of all the reflective constructs in this research has been established.

Table 6-6: HTMT Confidence Intervals Bias Corrected

	Original Sample (O)	Sample Mean (M)	Bias	2.50%	97.50%
ECC -> ACCES	0.726	0.73	0.004	0.6	0.853
ILIO -> ACCES	0.509	0.51	0.001	0.383	0.619
ILIO -> ECC	0.483	0.484	0.001	0.354	0.589
INCOMPA -> ACCES	0.518	0.519	0.001	0.381	0.638
INCOMPA -> ECC	0.506	0.508	0.002	0.36	0.633
INCOMPA -> ILIO	0.772	0.772	0	0.673	0.828
KA -> ACCES	0.438	0.451	0.013	0.343	0.532
KA -> ECC	0.434	0.443	0.009	0.31	0.542
KA -> ILIO	0.713	0.713	0	0.62	0.795
KA -> INCOMPA	0.751	0.752	0	0.662	0.825
LEEF -> ACCES	0.698	0.7	0.002	0.532	0.837
LEEF -> ECC	0.602	0.604	0.003	0.439	0.741
LEEF -> ILIO	0.651	0.65	0	0.549	0.747
LEEF -> INCOMPA	0.629	0.628	0	0.516	0.727
LEEF -> KA	0.253	0.256	0.002	0.113	0.403
MIO -> ACCES	0.328	0.338	0.01	0.211	0.451
MIO -> ECC	0.331	0.332	0.001	0.194	0.459
MIO -> ILIO	0.808	0.808	0	0.736	0.891
MIO -> INCOMPA	0.778	0.778	0	0.708	0.831
MIO -> KA	0.753	0.752	-0.001	0.65	0.844
MIO -> LEEF	0.546	0.545	-0.001	0.419	0.665
RELEV -> ACCES	0.639	0.644	0.005	0.555	0.77
RELEV -> ECC	0.775	0.779	0.003	0.574	0.924
RELEV -> ILIO	0.323	0.324	0.001	0.19	0.448
RELEV -> INCOMPA	0.374	0.375	0.001	0.235	0.499
RELEV -> KA	0.298	0.302	0.005	0.176	0.435
RELEV -> LEEF	0.557	0.559	0.002	0.374	0.712
RELEV -> MIO	0.206	0.213	0.007	0.093	0.336
SCAR -> ACCES	0.732	0.739	0.007	0.607	0.815
SCAR -> ECC	0.77	0.778	0.008	0.656	0.875
SCAR -> ILIO	0.366	0.369	0.003	0.23	0.484
SCAR -> INCOMPA	0.448	0.451	0.003	0.296	0.578
SCAR -> KA	0.431	0.442	0.011	0.308	0.549
SCAR -> LEEF	0.605	0.608	0.003	0.437	0.752
SCAR -> MIO	0.305	0.309	0.003	0.179	0.447
SCAR -> RELEV	0.735	0.739	0.004	0.645	0.858
SIO -> ACCES	0.332	0.339	0.007	0.214	0.457
SIO -> ECC	0.385	0.387	0.002	0.245	0.513
SIO -> ILIO	0.793	0.793	0	0.666	0.877
SIO -> INCOMPA	0.85	0.85	0	0.771	0.913
SIO -> KA	0.805	0.805	-0.001	0.711	0.883
SIO -> LEEF	0.509	0.508	-0.001	0.377	0.629
SIO -> MIO	0.913	0.913	0	0.843	0.95
SIO -> RELEV	0.184	0.192	0.008	0.073	0.331
SIO -> SCAR	0.36	0.362	0.002	0.209	0.498
SL -> ACCES	0.558	0.574	0.016	0.404	0.678
SL -> ECC	0.8	0.818	0.018	0.653	0.92
SL -> ILIO	0.434	0.442	0.008	0.303	0.547
SL -> INCOMPA	0.501	0.507	0.007	0.362	0.616
SL -> KA	0.435	0.445	0.009	0.309	0.545
SL -> LEEF	0.699	0.709	0.01	0.535	0.846
SL -> MIO	0.375	0.382	0.007	0.237	0.495
SL -> RELEV	0.667	0.681	0.014	0.592	0.723
SL -> SCAR	0.763	0.776	0.013	0.634	0.879
SL -> SIO	0.365	0.373	0.008	0.215	0.487
T&A -> ACCES	0.687	0.69	0.003	0.586	0.787
T&A -> ECC	0.554	0.556	0.002	0.428	0.666
T&A -> ILIO	0.791	0.791	0	0.691	0.874
T&A -> INCOMPA	0.774	0.774	0	0.67	0.864
T&A -> KA	0.734	0.734	0	0.671	0.78
T&A -> LEEF	0.402	0.403	0.001	0.254	0.544
T&A -> MIO	0.761	0.76	-0.001	0.65	0.857
T&A -> RELEV	0.505	0.507	0.002	0.358	0.626
T&A -> SCAR	0.611	0.615	0.004	0.487	0.722
T&A -> SIO	0.785	0.784	-0.001	0.676	0.876
T&A -> SL	0.527	0.535	0.008	0.397	0.649

6.2.2 Formative Constructs Analysis

For assessing the quality of formative measures in PLS-SEM, the statistical evaluation criteria and measurement procedures used for assessing reflective measures, such as the internal consistency reliability, convergent validity and discriminant validity, are inappropriate and meaningless (Hair et al., 2017). Because formative indicators are assumed to be error free. They are not necessarily correlated with each other, rather they are the composites that form the formative constructs (Kock, 2013). With PLS-SEM, there are three steps to assess the measurement model's quality involving formative indicators (Hair et al., 2017). The first step is to assess **convergent validity** of the formative constructs. The second step is to assess formative measurement models for **collinearity issues**. The third step is to assess **the significance and relevance** of the formative indicators. In this research, there are 13 formative measurement models: 1) *Inflexibility* (INFLEX); 2) *Cultural Misfits* (CM); 3) *Low Quality Downstream Information* (LQDI); 4) *Low Quality Upstream Information* (LQUI); 5) *Lack of Interactional Knowledge Inventory* (LIKI); 6) *Lack of Functional Knowledge Inventory* (LFKI); 7) *Lack of Environmental Knowledge Inventory* (LEKI); 8) *Trustful Environment within Organisation* (TEO); 9) *Trustful Relationship with Business Partners* (TRP); 10) *Knowledge Selection* (KS); 11) *Knowledge Generation* (KG); 12) *Knowledge Internalisation* (KI); 13) *Knowledge Externalisation* (KE).

Convergent validity test

"*Convergent validity is the extent to which a measure correlates positively with other (e.g., reflective) measures of the same construct using different indicators*" (Hair et al., 2017, p.140). Therefore, when conducting analysis for formative measurement models, it is necessary to test whether the formative indictors are highly correlated with a reflective measure of the same construct (Hair et al., 2017). This type of test is also known as redundancy analysis (Chin, 1998b). The purpose of redundancy analysis is to prevent the information in the model being redundant in the sense that the information is included in the formative construct and again in the reflective one. The strength of the path coefficient between the two constructs is indicative of the validity of the designated set of formative indicators. A value of 0.80, or at a minimum 0.70 and above, is desired (Nunnally, 1978). If lack of convergent validity (i.e., the value of path coefficient is less than 0.70), it means that the indictors of the formative construct do not contribute at a sufficient degree to its intended content, then the formative construct needs to be refined by adding and/or exchanging indicators (Hair et al., 2017).

There are two approaches to conducting redundancy analysis (Hair et al., 2017). The first one is to add sets of reflective multi-item measures into the formative construct, and then analyse the path coefficient between the formative measures and reflective measures of the construct. However, this approach has two major drawbacks. Firstly, established and suitable reflective measurement items may not be available, and constructing a new scale is time-consuming and difficult. Secondly, including additional sets of reflective multi-item measures would increase the survey length. Long surveys are likely to result in respondent exhaustion, hence decreasing response rates and increasing the number of missing values. This research adopted another approach which is to use a global item that summarises the essence of the formative indicators of a construct (Sarstedt et al., 2013). This question is only used as an endogenous/dependent single-item construct in redundancy analysis in order to validate its related formative construct. It will not be used in other analyses (Hair et al., 2017).

The survey questionnaire of this research contained thirteen global single-item measures with generic assessments of the thirteen formative constructs mentioned above in the beginning of this section (see **Table 6-7**), these global single-items were used as measures of the dependent constructs in the redundancy analyses.

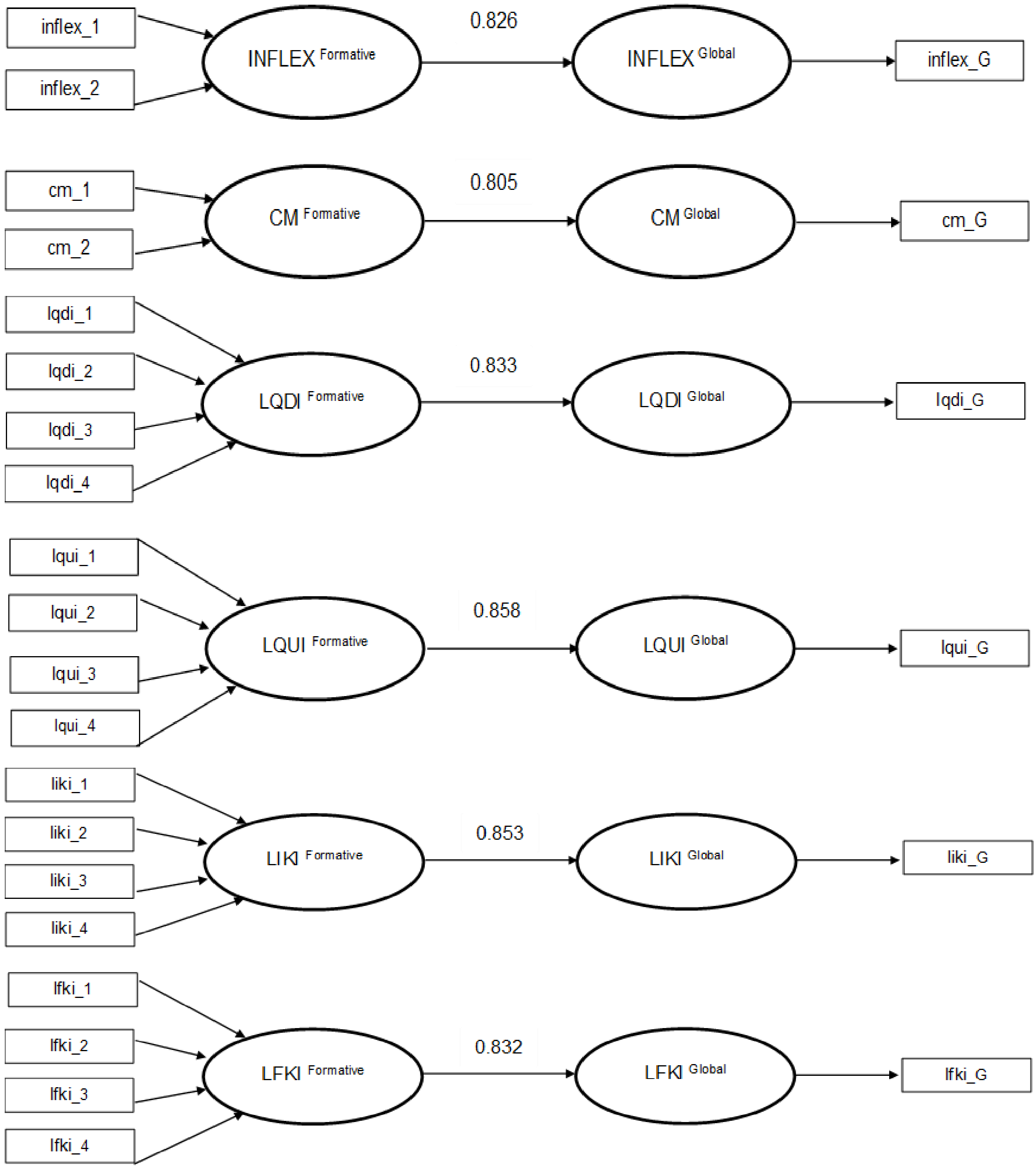
Table 6-7: Global Items for Redundancy Analyses

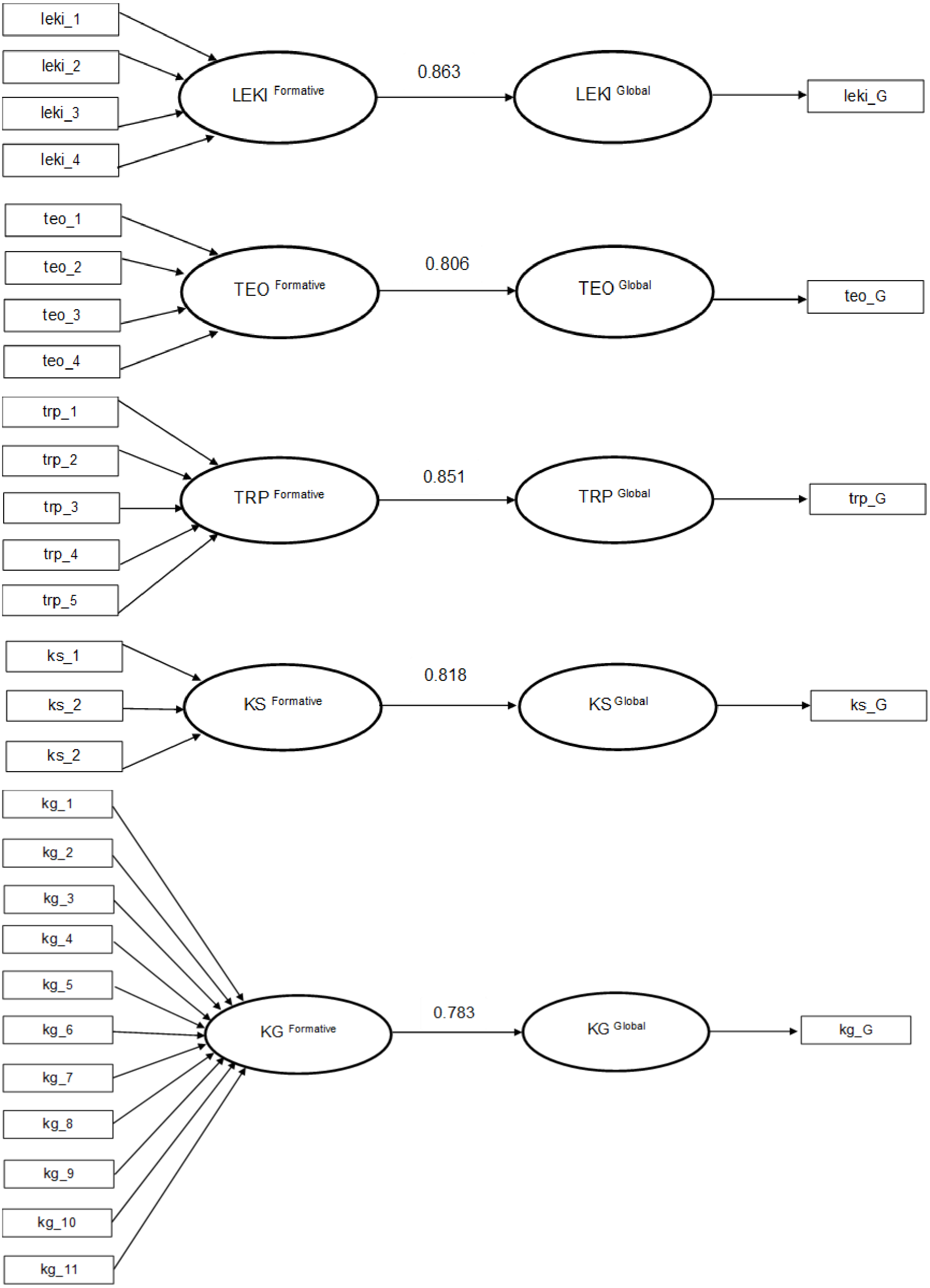
Formative Constructs	Global Items
Inflexibility (INFLEX)	Our information systems are not flexible to accommodate any change in our business operation.

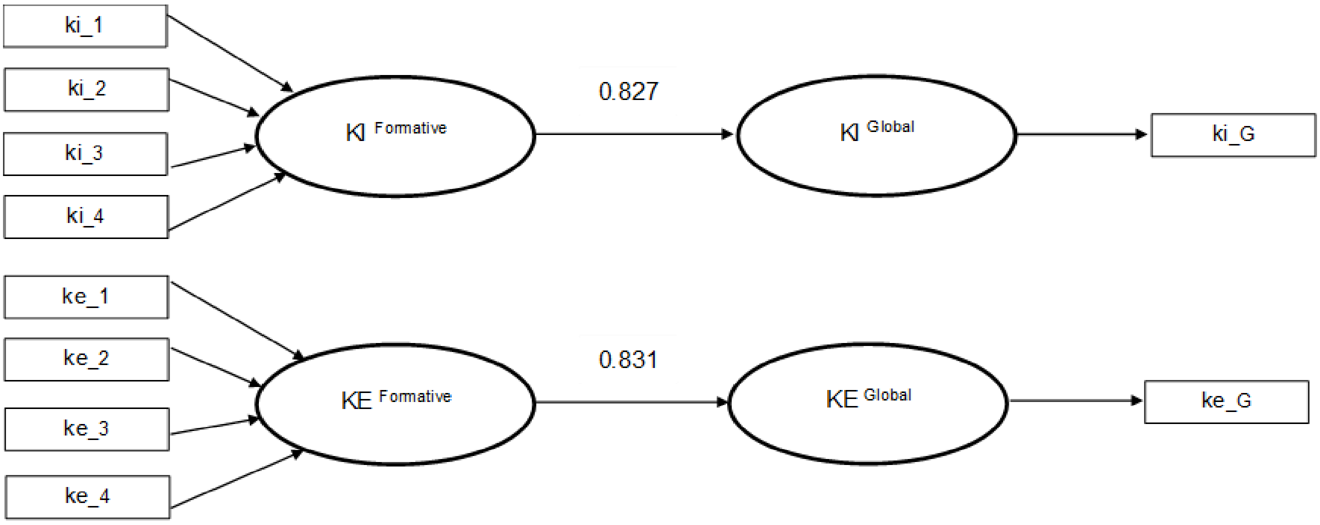
Cultural misfits (CM)	The information systems used in our company are not localized enough.
Low quality downstream information (LQDI)	The quality of the information we get from the downstream of our supply chain is poor.
Low quality upstream information (LQUI)	The quality of the information we get from the upstream of our supply chain is poor.
Lack of interactional knowledge inventory (LIKI)	We have very little knowledge and experience in effectively interacting with trading partners.
Lack of functional knowledge inventory (LFKI)	We have very little knowledge and experience in effectively working with supplier in production.
Lack of environmental knowledge inventory (LEKI)	We have very little outside knowledge and information which could affect our business.
Trustful environment within organization (TEO)	I trust my colleagues
Trustful relationship with business partners (TRP)	Our company and trading partners trust each other.
Knowledge selection (KS)	We can always find right information and knowledge inside our company to solve problems.
Knowledge generation (KG)	We can always make effective decisions and plans for our business operation.
Knowledge internalization (KI)	We can always utilize information and knowledge effectively and efficiently in our company.
Knowledge externalization (KE)	Our products and services are successful in the market.

Figure 6-2 shows the results of the redundancy analysis for the thirteen formative constructs. The original formative construct is labelled as, for example, INFLEX $^{\text{Formative}}$, whereas the corresponding single-item construct is labelled as INFLEX $^{\text{Global}}$. As can be seen, the lowest path coefficient yielded by this analysis is 0.783 from KG, which is above the recommended threshold of 0.70, hence providing support for all formative constructs' convergent validity.

Figure 6-2: Redundancy Analysis Assessment of Formative Constructs




leki_1
leki_2
leki_3
leki_4
LEKI Formative
0.863
LEKI Global
leki_G
teo_1
teo_2
teo_3
teo_4
TEO Formative
0.806
TEO Global
teo_G
trp_1
trp_2
trp_3
trp_4
trp_5
TRP Formative
0.851
TRP Global
trp_G
ks_1
ks_2
ks_2
KS Formative
0.818
KS Global
ks_G
kg_1
kg_2
kg_3
kg_4
kg_5
kg_6
kg_7
kg_8
kg_9
kg_10
kg_11
KG Formative
0.783
KG Global
kg_G



Collinearity test

The purpose of this step is to examine whether there are high correlations (also called collinearity) existing between two formative indicators. Unlike reflective indicators, which can be interchanged, high correlations are not expected between indicators in formative measurement models. In fact, high level of collinearity between formative indicators can cause serious problem because they have an impact on the estimation of weights and their statistical significance, consequently the analytic results will be disrupted (Hair et al, 2017). To assess the level of collinearity, researchers should check the variance inflation factor (VIF). There are two views about the threshold level of VIFs, while some researchers recommended that VIFs should be lower than 5 or 3.3 (conservative view) (Hair et al., 2011), others suggested a more liberal threshold of 10 (Kaleka, 2012; Kock, 2013). If the level of collinearity exceeds the suggested threshold, the researcher should consider removing one of the corresponding indicators (Hair, et al., 2017). According to the results in **Table 6-8** and **Table 6-9**, kg_11 has the highest VIF value (3.676). Hence, VIF values are all below the threshold value of 5. Therefore, collinearity does not reach critical level in any of the formative constructs and suggests a good validity for the further analysis of the model.

Table 6-8: Variance Inflation Factor (VIF)

	VIF
cm_1	1.043
cm_2	1.043
inflex_1	1.169
inflex_2	1.169
ke_1	1.499
ke_2	2.226
ke_3	1.877
ke_4	1.568
kg_1	2.938
kg_10	2.565
kg_11	3.676
kg_2	2.542
kg_3	1.823
kg_4	2.352
kg_5	2.069
kg_6	3.074
kg_7	3.085
kg_8	2.454
kg_9	3.359
ki_1	1.974
ki_2	1.956
ki_3	1.232
ki_4	1.154
ks_1	1.027
ks_2	1.083
ks_3	1.06

Table 6-9: Variance Inflation Factor (VIF)

	VIF
leki_1	1.951
leki_2	2.14
leki_3	1.591
leki_4	1.704
lfki_1	2.427
lfki_2	1.985
lfki_3	1.93
lfki_4	1.639
liki_1	2.321
liki_2	2.165
liki_3	1.257
liki_4	2.102
lqdi_1	2.295
lqdi_2	1.835
lqdi_3	1.337
lqdi_4	2.366
lqui_1	1.913
lqui_2	1.61
lqui_3	1.374
lqui_4	1.773
teo_1	1.136
teo_2	1.174
teo_3	1.054
teo_4	1.123
trp_1	1.215
trp_2	1.091
trp_3	1.175
trp_4	1.162
trp_5	1.227

Significance and relevance test

To ensure content validity of formative indicators, the composite measures selected by the researcher for a formative construct should capture the full domain of the construct (Petter et al., 2007). In order to see whether a formative indicator truly contributes to forming its corresponding construct, researchers need to use the bootstrapping procedure to test if the indicators' outer weights in formative measurement models are significantly different from zero (i.e. p value <0.05 or < 0.1, at significance level=5% and 10%, respectively), and the indicators' outer loadings need to be above 0.5. If both indicator's weight and loading are non-significant, it would mean that the indicator does not contribute to forming the construct it intends to do and thus could be considered for elimination (Cenfetelli and Brasselier, 2009; Hair, et al., 2017). In addition to the contribution test, it is worth reporting the bootstrap confidence interval as it provides additional information regarding how stable the coefficient estimate is. If the confidence interval of a coefficient between an indicator and its latent variable is narrower (i.e. not including zero), then its stability is higher (Hair, et al., 2017). **Appendix I** shows that there are five indicators' p values that have exceeded the threshold value of 0.1. However, their outer loadings are all above 0.5, the smallest one is 0.533 from the lqdi_3 to LQDI. According to Hair et al. (2017), when an indicator's outer weight is non-significant but its outer loading is above 0.5, then it means that the indicator should be interpreted as absolutely important but not as relatively important. In this case, these five indicators will still be retained for further analysis.

6.2.3 High-Order Constructs Analysis

The evaluation of the high-order constructs (HOC) is similar to that of the low order constructs (LOC). All constructs in the HCM need to meet all standard measurement model evaluation criteria. However, unlike analyzing a normal measurement model, the evaluation of the HOC is not concerned with the relationship between the HOC and its indicator variables but the relationships between the HOC and its LOCs. There are four types of HOC, which are reflective-reflective, formative-reflective, reflective-formative and formative-formative (Hair et al. 2017). In this research, see **Table 6-10**, there are six second-order variables and twenty first-order components. All the HOCs are formed by the LOCs in formative-formative and reflective-formative hierarchical component models, which is similar to formative measurement model analysis. Therefore, to analysis these types of HOCs, the researcher also needs to assess collinearity (VIF value) as well as significance (p value) and relevance (total effect) of the relations between the LOCs and the HOCs (Hair et al. 2017). The **Table 6-11** and **Table 6-12** present the first order components' VIFs and second order formative variables' significances, respectively. As it can be noticed, all p values and VIFs are lower than the threshold. Hence, there is no collinearity problem in all HOCs and every first order component is statistically significant to its associated second order variable. In addition, from **Table 6-13** it can be seen that the total effects of the first order variables (rows) under the same second order construct (columns) are very similar to each other, thus have equal relevance for forming the HOCs.

Table 6-10: First and Second Order Constructs

Second Order Variables	**First Order Components**
Information Overload (IO)	➢ Supplier information overload (SIO) ➢ Market information overload (MIO) ➢ Internal legacy information overload (ILIO)
Inappropriate Information System (IIS)	➢ Incompatibility (INCOMPA) ➢ Lack of extended enterprise function (LEEF) ➢ Inflexibility (INFLEX) ➢ Cultural misfits (CM)
Low Quality Information (LQI)	➢ Low quality downstream information (LQDI) ➢ Low quality upstream information (LQUI)
Insufficient Knowledge Inventory (IKI)	➢ Lack of interactional knowledge inventory (LIKI) ➢ Lack of functional knowledge inventory (LFKI) ➢ Lack of environmental knowledge inventory (LEKI)
Identification and Usage of Valuable Information and Knowledge (IUVI)	➢ Relevancy (RELEV) ➢ Timeliness and accuracy (T&A) ➢ Scarcity (SCAR) ➢ Accessibility (ACCES)
Encouraging Information and Knowledge Flow (EIKF)	➢ Trustful environment within organization (TEO) ➢ Trustful relationship with business partners (TRP) ➢ Shared language (SL) ➢ Expanding communication channel (ECC)

Table 6-11: First Order Constructs' VIF

	EIKF	IIS	IKI	IO	IUVI	LQI
ACCES					2.655	
CM		1.925				
ECC	1.854					
ILIO				2.969		
INCOMPA		2.765				
INFLEX		2.901				
LEEF		1.441				
LEKI			3.092			
LFKI			4.842			
LIKI			2.871			
LQDI						4.337
LQUI						4.337
MIO				4.057		
RELEV					2.116	
SCAR					1.932	
SIO				4.797		
SL	1.871					
T&A					1.502	
TEO	1.915					
TRP	2.429					

Table 6-12: Significance Test for HOCs

	P Values
ACCES -> IUVI	0
CM -> IIS	0
ECC -> EIKF	0
ILIO -> IO	0
INCOMPA -> IIS	0
INFLEX -> IIS	0
LEEF -> IIS	0
LEKI -> IKI	0
LFKI -> IKI	0
LIKI -> IKI	0
LQDI -> LQI	0
LQUI -> LQI	0
MIO -> IO	0
RELEV -> IUVI	0
SCAR -> IUVI	0
SIO -> IO	0
SL -> EIKF	0
T&A -> IUVI	0
TEO -> EIKF	0
TRP -> EIKF	0

Table 6-13: Relevance Test for HOCs

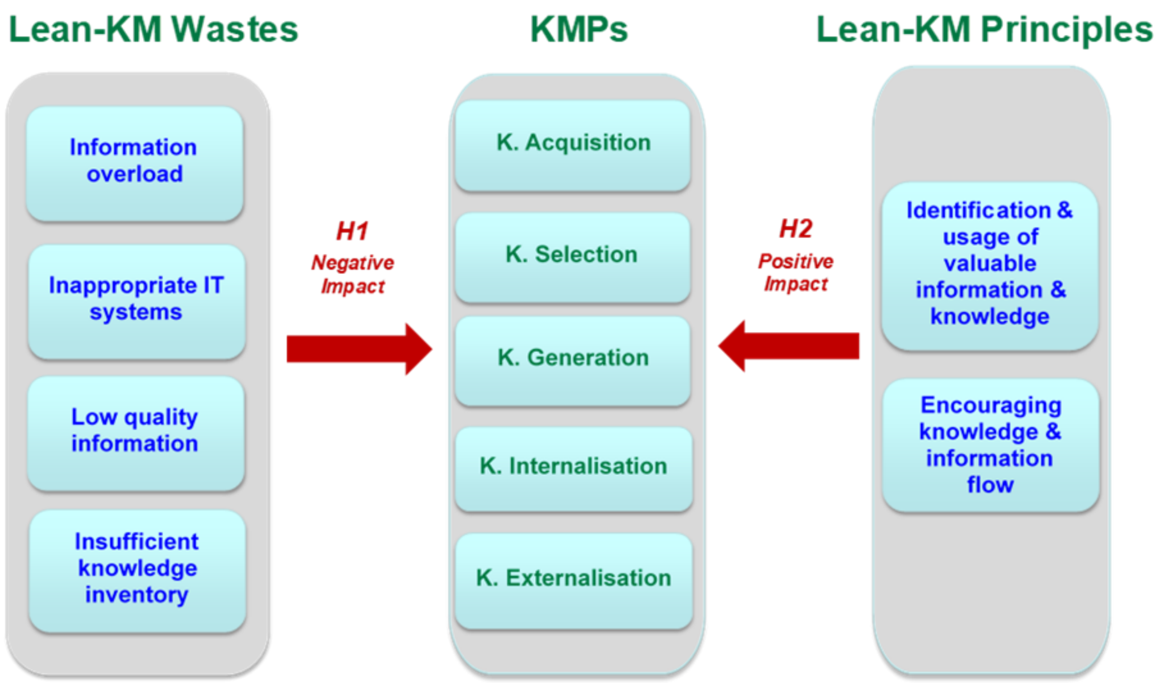
	EIKF	IIS	IKI	IO	IUVI	LQI
ACCES					0.301	
CM		0.438				
ECC	0.332					
ILIO				0.353		
INCOMPA		0.401				
INFLEX		0.447				
LEEF		0.445				
LEKI			0.36			
LFKI			0.328			
LIKI			0.354			
LQDI						0.494
LQUI						0.536
MIO				0.355		
RELEV					0.328	
SCAR					0.324	
SIO				0.358		
SL	0.302					
T&A					0.389	
TEO	0.389					
TRP	0.387					

6.2.4 Path Model Analysis

Hair et al. (2017) acknowledge that a reliable and valid measurement model is the basis of an accurate estimate of the structural model. After confirming the reliability and validity of the construct measures (reflective, formative and HOCs) in the previous section, the next step will address the assessment of the structural model results. The structure model represents the underlying structural theories/concepts of the research. Assessment of the structural model results enables the researcher to discover the model's capability to predict one or more target/dependent constructs (Garson, 2016). The assessment procedures include examining the model's predictive capabilities and the relationships between the constructs. There are six steps to assess the structural model: (step 1) assess structural model for collinearity issues, (step 2) assess the significance and relevance of the structural model relationships, (step 3) assess the level of the predictive accuracy R^2, (step 4) assess the f^2 effect size, (step 5) assess the predictive relevance Q^2, and (step 6) assess the q^2 effect size (Hair et al., 2017). The reason for examining collinearity (step 1) of the structural model is that the estimation of path coefficients in the structural model is based on ordinary least squares (OLS) regressions of each endogenous latent variable on its corresponding predecessor constructs, the path coefficients, hence, it might be biased if the estimation involves critical levels of collinearity among the predictor constructs or the independent variables. In addition, when examining the structural model in CB-SEM, usually researchers are advised to conduct various model fit test, such as *goodness-of-fit index*, *the chi-square (X^2) test* and *the root mean square residual covariance (RMS_{theta})*, in order to judge how well a hypothesized model structure fits the empirical data and identify model misspecifications (Byrne, 2010; Schumacker and Lomax, 2010; Wong, 2019). However, due to the algorithm mechanism these model fit measures cannot be fully applied in PLS-SEM. For this reason, Sarstedt et al. (2014) suggested that instead of testing the overall goodness of the model fit, the structural model should be assessed in terms of how well it predicts the endogenous constructs. The significance of the path coefficients (step 2), the level of the R^2 values (step 3), the f^2 effect size (step 4), the predictive relevance Q^2 (step 5), and the q^2 effect size (step 6) are key criteria for testing the relationships between the constructs and the model's predictive capabilities in PLS-SEM (Hair et al., 2017). In the following paragraphs, each step will be illustrated in greater detail.

Figure 6-3 shows the hypothesized structural model, illustrating the latent constructs of the current study. In this study, the structural model examines the negative impacts on knowledge production process (i.e. *knowledge acquisition* KA, *knowledge selection* KS, *knowledge generation* KG, *knowledge internalization* KI, and *knowledge externalization* KE) from the four lean wastes (i.e. *informative overload* IO, *low quality information* LQI, *inappropriate IT system* IIS, and *insufficient knowledge inventory* IKI), and also examines the positive impacts from two lean principles (i.e. *identification and usage of valuable information & knowledge* IUVI, and *encouraging information and knowledge flow* EIKF).

Figure 6-3: First and Second Order Structural Model



Step 1: collinearity assessment

To assess structural model's collinearity, the same measures as in the evaluation of formative measurement model will be applied. In doing so, the researcher needs to examine each set of predictor constructs (i.e. second order constructs in this project) separately in their associated dependent variables of the structural model. A VIF value above 5 in predictor constructs is considered as the critical level of collinearity. If a construct's VIF exceeds the threshold, it should be eliminated, or be merged into a higher-order construct to solve the collinearity problem (Hair et al., 2017). **Table 6-14** shows that there is no collinearity issue in this study, all predictor constructs' VIF values are less than 5, which means that every predictor construct represents a unique meaning and they cannot be interchanged with each other.

Table 6-14: Collinearity in the Structural Model

	KA	KE	KG	KI	KS
EIKF	1.796		1.896	1.77	
IIS	1.607	1.547	3.079	1.532	
IKI	1.085	3.671	3.675		
IO			2.846		1.431
IUVI	1.965	1.498	2.225	1.928	1.431
LQI		3.589	3.636		

Step 2: structural model path coefficients

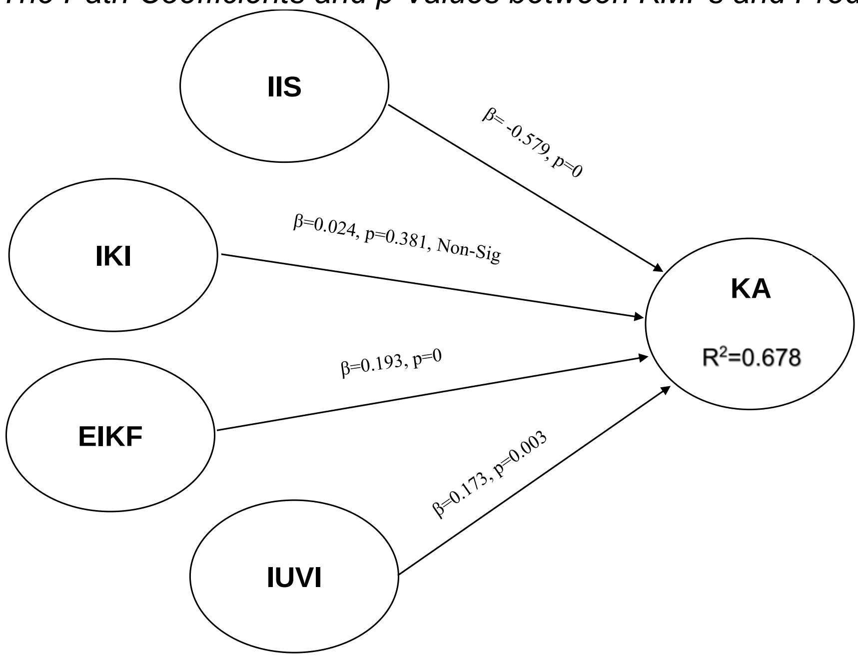
The structural model (inner model) is used to measure the causal relationships among the constructs, and these relationships among latent variable are hypothesised, linked with the literature review, and justified. To analyse the structural model, research should test path coefficients and significances (e.g. p values) between independent variables and dependent variables (Henseler et al., 2009; Kock, 2012). The path coefficients (β) represent the hypothesized relationships among the constructs. They have standardized values approximately between -1 and +1. The closer the estimated values are to +1, the stronger positive relationships the path coefficients are (and vice versa for negative values). The closer the path coefficients are to 0, the weaker the relationships are (Hair et al., 2017). Therefore, if one path coefficient is larger than another, its effect on the dependent latent variable is greater. In addition, the p value associated with each path coefficient is important for the purpose of examining hypotheses. The p value not only shows the power of the relationship which is already given by the path coefficient itself, but also indicates the extent to which the independent variable is associated with the dependent variable. According to Hair et al. (2017), if the path coefficient has a significance of p value less than 0.01 (significance level = 1%), 0.05 (significance level = 5%) or 0.1 (significance level = 10%) (liberal standard), then the hypothesized relationship between constructs is supported by empirical data.

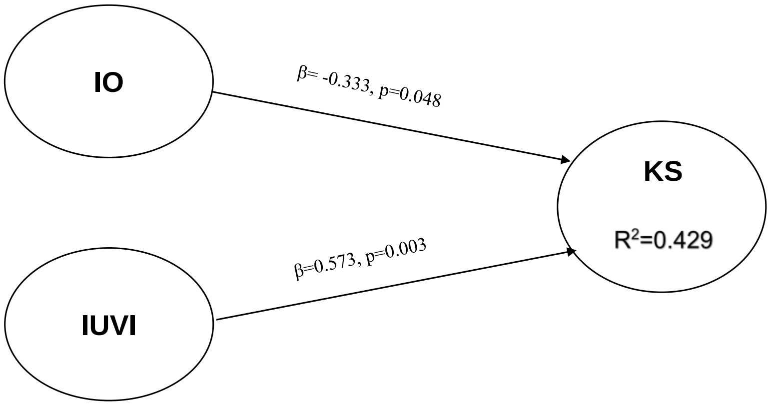
The results of the data analysis of the structural model are presented in **Figure 6-4**. The arrows and adjacent values illustrate the effect between the latent variables and their path coefficients, including their p values. R^2 values show the coefficient of determination of dependent latent variables in the structural model, see below for further explanation (Hair et al., 2017). These values are displayed in the dependent latent variables.

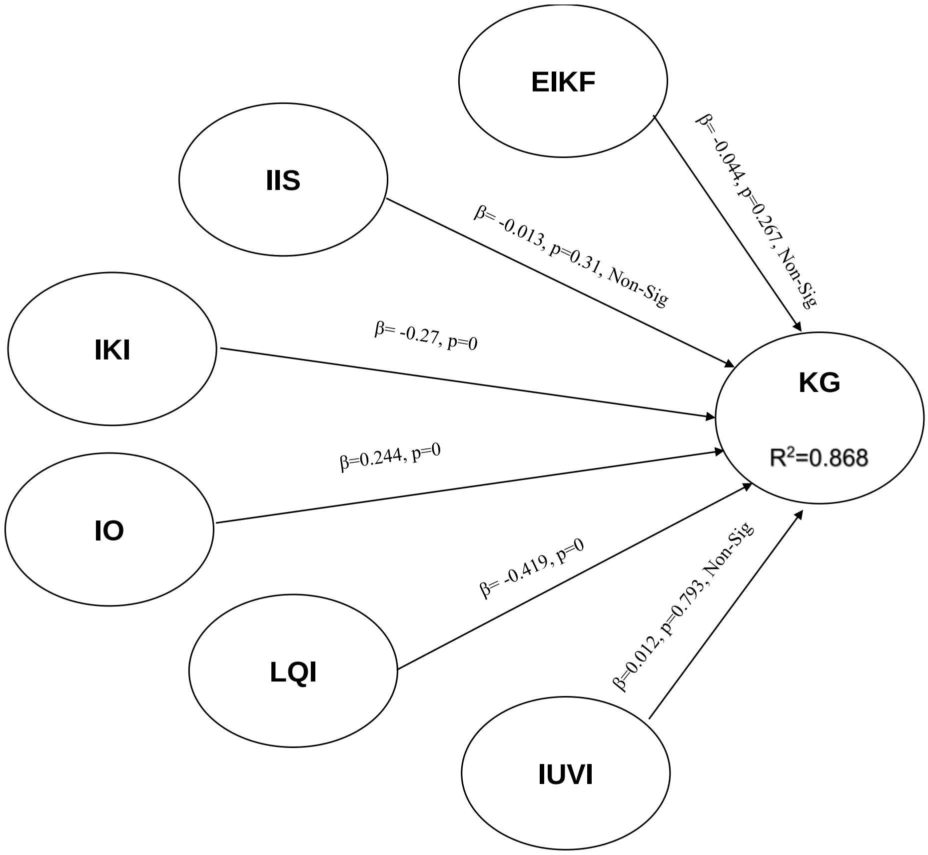
With respect to the *Knowledge Acquisition* (KA), **Figure 6-4** illustrates that the variable *Encouraging Information and Knowledge Flow* (EIKF) has the strongest positive impact (β= 0.193, p= 0), followed by the variable *Identification and Usage of Valuable Information and Knowledge* (IUVI) (β= 0.173, p= 0.003).

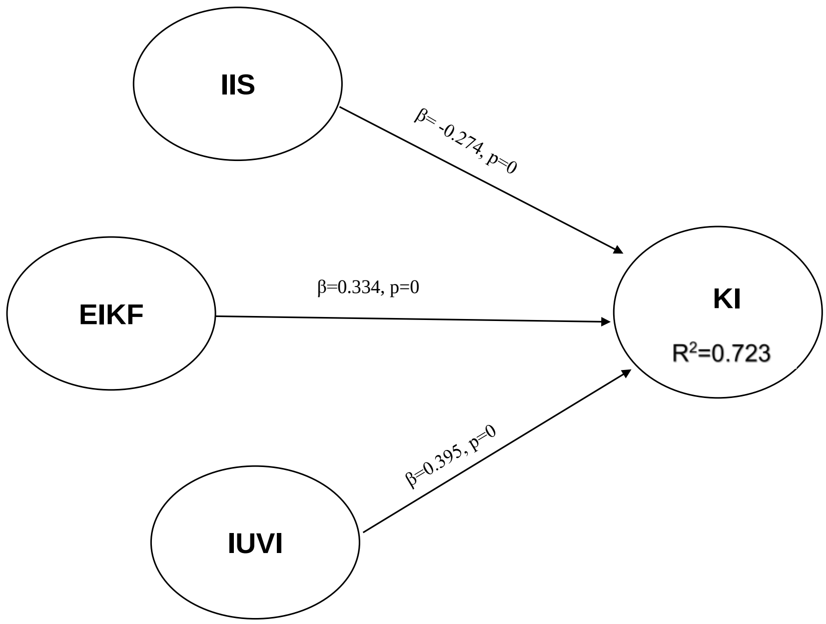
The variable *Insufficient Knowledge Inventory* (IKI) has statistically non-significant effects. In addition, the variable *Inappropriate Information System* (IIS) has a negative impact on *Knowledge Acquisition* (KA) (β= -0.579, p= 0). Regarding to *Knowledge Selection* (KS), IUVI has a positive impact (β= 0.573, p= 0.003), and the variable *Information Overload* (IO) has a negative significant effect on KS (β= -0.333, p= 0.048). As for *Knowledge Generation* (KG), three predictors: EIKF, IIS and IUVI have very weak and statistically non-significant effects (β= -0.044, -0.013 and 0.012, p>0.1 respectively). The variable *Low Quality Information* (LQI) has the strongest negative impact (β= -0.419, p= 0), follow by IKI (β= -0.27, p= 0). Furthermore, it is important to highlight that IO has a positive significant impact on KG (β= 0.244, p= 0). This result is contrary to the theoretical expectation. With regard to *Knowledge Internalization* (KI), EIKF has the strongest impact (β= 0.634, p= 0), followed by IUVI (β= 0.395, p= 0). IIS has a negative impact on KI (β= -0.274, p= 0). Lastly, concerning *Knowledge Externalisation* (KE), IIS's impact is weak and statistically non-significant (β= -0.017, p= 0.218). LQI and IKI have negative effect (β= -0.438 and -0.386, p= 0, respectively). IUVI has a positive impact on KE (β= 0.324, p= 0.011).

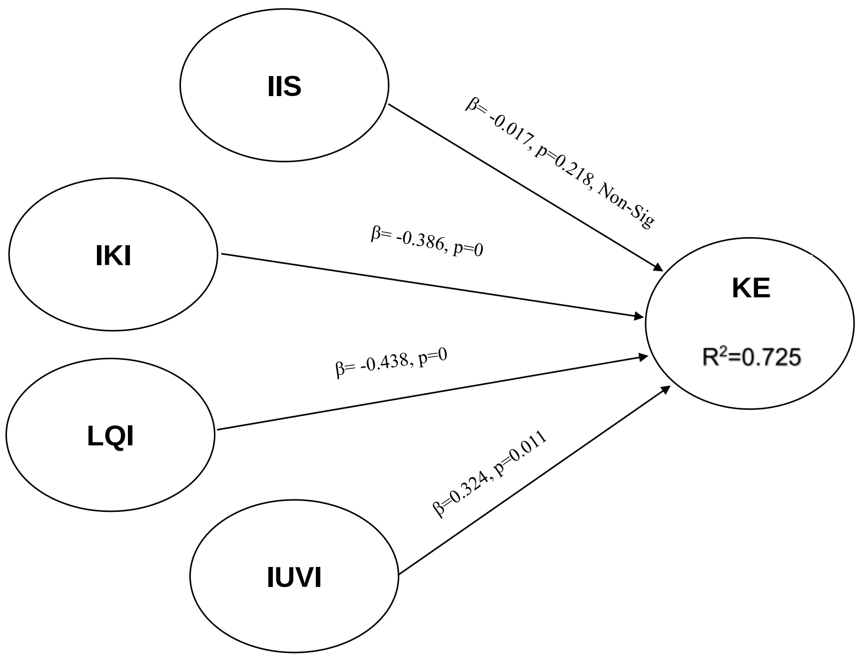
Figure 6-4: The Path Coefficients and p Values between KMPs and Predictors




IO
β= -0.333, p=0.048
KS
R2=0.429
β=0.573, p=0.003
IUVI


EIKF
β= -0.044, p=0.267, Non-Sig
IIS
β= -0.013, p=0.31, Non-Sig
IKI
β= -0.27, p=0
KG
R2=0.868
β=0.244, p=0
IO
β= -0.419, p=0
β=0.012, p=0.793, Non-Sig
LQI
IUVI





Step 3: coefficient of determination (R^2 value)

The coefficient of determination (R^2 value) is the most commonly used measure for evaluation of the structural model. It is a measure of the model's predictive accuracy and is calculated as the squared correlation between a specific dependent construct's actual and predicted values (Hair et al., 2017). *"The coefficient represents the exogenous latent variables' combined effects on the endogenous latent variable. That is, the coefficient represents the amount of variance in the endogenous constructs explained by all of the exogenous* *constructs linked to it*" (Hair et al., 2017, p.198). In other words, the greater is the R^2 values, the better the latent variable is predicted by the constructs pointing at it in the structural model. The range of R^2 value is between 0 and 1, with higher value indicating higher value of predictive accuracy. However, the exact interpretation of the R^2 value depends on the particular model and research discipline. For instance, Roldán and Sanchez-Franco (2012) recommend that R^2 value should be at least 0.10 considered as a weak effect. Henseler et al. (2009) suggested that R^2 values of 0.65, 0.33, or 0.19 for the endogenous construct can be described as substantial, moderate, and weak respectively. However, from a more liberal point of view, Hair et al. (2017) recommend interpreting R^2 measure of an endogenous construct in the inner path model as substantial 0.75, moderate 0.50, and weak 0.25. As a consequence, it is also recommended that researchers should report path coefficients and their associated significance (p values).

From **Table 6-15**, the interpretation of the R^2 values of the dependent variables is as follows, the prediction of the *Knowledge Generation* (KG) is substantial (R^2= 0.868). The prediction of the *Knowledge Internalisation* (KI) and *Knowledge Externalisation* (KE) is close to substantial (R^2= 0.723 and 0.725 respectively), whereas the relationships between the KI and all its predictors are statistically significant. Moreover, the prediction of the *Knowledge Acquisition* (KA) and *Knowledge Selection* (KS) is moderate and close to moderate respectively (R^2= 0.675 and 0.426). Overall, all the dependent variables are explained very well by their associated predictors. Most of these relationships can be considered as statistically meaningful.

Table 6-15: Path Coefficients, p Values and R Squares

	Path Coefficients	p-Values	R^2	Description
EIKF→KA	0.193	0	0.678	Positive， significant, and moderate
IIS→KA	-0.579	0	0.678	Negative, significant, and moderate
IKI→KA	0.024	0.381	0.678	Non-significant
IUVI→KA	0.173	0.003	0.678	Positive， significant, and moderate
IO→KS	-0.333	0.048	0.429	Negative, significant, and moderate
IUVI→KS	0.573	0	0.429	Positive， significant, and moderate
EIKF→KG	-0.044	0.267	0.868	Non-significant
IIS→KG	-0.013	0.31	0.868	Non-significant
IKI→KG	-0.27	0	0.868	Negative， significant, and substantial
IO→KG	0.244	0	0.868	Positive， significant, and substantial
IUVI→KG	0.012	0.793	0.868	Non-significant
LQI→KG	-0.419	0	0.868	Negative， significant, and substantial
EIKF→KI	0.334	0	0.723	Positive， significant, and substantial
IIS→KI	-0.274	0	0.723	Negative， significant, and substantial
IUVI→KI	0.395	0	0.723	Positive， significant, and substantial
IIS→KE	-0.017	0.218	0.725	Non-significant
IKI→KE	-0.386	0	0.725	Negative， significant, and substantial
IUVI→KE	0.324	0.011	0.725	Positive， significant, and substantial
LQI→KE	-0.438	0	0.725	Negative， significant, and substantial

Step 4: effect size (f^2)

In addition to assessing the R^2 values of all dependent constructs, the change in the R^2 value when a specified independent construct is deleted from the model can be used to evaluate whether the deleted construct has a substantial impact on the dependent constructs. This measure is referred as the f^2 effect size. The effect size can be calculated as : $f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$, where $R^2_{included}$ and $R^2_{excluded}$ are the R^2 values of the dependent construct when a selected independent construct is included in or excluded from the model (Hair et al., 2017). The f^2 values of 0.02, 0.15, and 0.35 can be considered as small, medium, and large effects of the independent latent variables (Roldán and Sanchez-Franco, 2012). Values below 0.02 indicate that the effects are too small to be considered relevant from a practical point of view.

Table 6-16 reports the values for the independent variables' effect sizes. It can be seen that the effect size of *the variable Encourage Information and Knowledge Flow* (EIKF) on the *Knowledge Internalisation* (KI) is medium, on *Knowledge Acquisition* (KA) is small, and it has no effect on Knowledge

Generation (KG). As for the variable *Inappropriate Information System* (IIS), it has large contribution to KA's predictive accuracy and medium to KI's predictive accuracy, whereas its contributions to *KG* and *Knowledge Externalisation* (KE)'s predictive accuracy are too small. With respect to the variable *Insufficient Knowledge Inventory* (IKI), it has no effect on KA. To KG and KE, its effect sizes are close to medium and medium (f^2= 0.149 and 0.265, respectively). Regarding to the *Information Overload* (IO), its effect sizes for both *Knowledge Selection* (KS) and *KG* 's predictive accuracy are small and medium, respectively. As for the variable *Identification and Usage of Valuable Information and Knowledge* (IUVI), it has a large effect on KS, close to large effect on KI, and no effect on KG. To KA and KE's predictive accuracy, its effect sizes are close to medium and medium respectively. Finally, regarding the variable Low Quality Information (LQI), it has large effects on both KG and KE's predictive accuracy.

Table 6-16: The Effect Sizes

	Effect Size (f^2)	Description
EIKF→KA	0.065	Small
EIKF→KG	0.008	Too Small
EIKF→KI	0.227	Medium
IIS→KA	0.649	Large
IIS→KG	0.004	Too Small
IIS→KI	0.177	Medium
IIS→KE	0.01	Too Small
IKI→KA	0.002	Too Small
IKI→KG	0.149	Close to Medium
IKI→KE	0.265	Medium
IO→KS	0.022	Small
IO→KG	0.158	Medium
IUVI→KA	0.148	Close to Medium
IUVI→KS	0.402	Large
IUVI→KG	0	Too Small
IUVI→KI	0.292	Close to Large
IUVI→KE	0.188	Medium
LQI→KG	0.366	Large
LQI→KE	0.533	Large

Step 5: Blindfolding and predictive relevance (Q^2)

Henseler et al. (2009) and Hair et al. (2017) stressed the importance of reporting the Stone-Geisser's Q^2 value. According to Hair et al. (2017), it is an indicator of the model's out-of-sample predictive power or predictive relevance. The Q^2 value of a specific dependent latent variable larger than 0 means that the path model has good predictive relevance for a particular dependent construct (Henseler et al., 2009; Hair et al., 2017). The Q^2 value can be calculated by using the blindfolding procedure for a specified omission distance. Usually, the omission distance D between 5 and 10 should be applied; making sure that the number of observations used in the model estimation divided by the omission distance D is not an integer (Hair et al., 2017). In this research, among the 359 observations, 7 will be selected as the omission distance for this study. Blindfolding procedure is usually applied to reflective dependent latent constructs as well as to dependent single-item constructs (Hair et al., 2017). In this research, *Knowledge Acquisition* (KA) is the only endogenous/dependent construct that has a reflective measurement model in the whole path model. **Table 6-17** shows that Q^2 of KA is larger than 0, which means that the path model has good predictive relevance for KA.

Table 6-17: Predictive Relevance Q^2 of the Knowledge Acquisition

	SSO	SSE	Q^2 (=1-SSE/SSO)
KA	1,436.00	768.029	0.465

Step 6: effect size (q^2)

The purpose of the effect size q^2 is to assess a dependent construct's contribution to an independent latent variable's Q^2 value. Similar to the f^2 effect size approach for assessing R^2 values, the q^2 effect size can be calculated as: $q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$. The q^2 values of 0.02, 0.15, and 0.35 indicate that an independent construct has small, medium, or large predictive relevance for a certain dependent latent variable respectively (Hair et al., 2017). In this research, the Knowledge Acquisition (KA) has four predictors: *Encouraging Information and Knowledge Flow* (EIKF), *Inappropriate Information System* (IIS), *Insufficient Knowledge Inventory* (IKI), and *Identification and Usage of Valuable Information and Knowledge* (IUVI). According to the results in **Table 6-18**, IIS has a large effect size on KA's predictive relevance. EIKF and IUVI have small effect on KA, and IKI has no effect on KA.

Table 6-18: Effect Size q^2

	Effect Size (q^2)	Description
EIKF -> KA	0.02	Small
IIS -> KA	0.299	Close to Large
IKI -> KA	-0.007	No Effect
IUVI -> KA	0.021	Small

Further Analysis

Further analysis includes two parts. In the first part, the relative importance of each exogenous construct to their associated dependent variables will be examined and ranked. By doing so, researchers are able to find out which driver construct has the strongest impact on a certain dependent variable. The second part is to evaluate the total effects of each sub-dimension (e.g. first order constructs) within the higher order constructs. According to Hair et al. (2017), the total effects indicates how strongly each of the first order driver construct ultimately influences the target variables (i.e. knowledge management processes). Therefore, assessing the constructs' importance and sub factors' total effects can be used to enhance company's managerial performance.

Table 6-19 presents the relative importance of each positive effect construct to its target dependent variables. It can be seen that the variable *Identification and Usage of Valuable Information and Knowledge* (IUVI) is the primary driver for *Knowledge Selection* (KS), *Knowledge Internalization* (KI) and *Knowledge Externalization* (KE). Also, the variables *Encourage Information and Knowledge Flow* (EIKF) and the *Information Overload* (IO) are most important factors for the *Knowledge Acquisition* (KA) and *Knowledge Generation* (KG), respectively. **Table 6-20** illustrates the relative importance of each negative effect construct to its target dependent variables. As can be seen from the results, the variable *Inappropriate Information System* (IIS) is the most important negative factor for the KA and KI. For KG and KE, the variable *Low Quality Information* (LQI) is the biggest negative factor. Moreover, the variable *Information Overload* (IO) is the only one that has negative impact to KS.

Table 6-19: The Relative Importance Ranking for the Positive Factors

	Relative Importance (+)	Rank
EIKF→KA	0.193	1
IUVI→KA	0.173	2
IUVI→KS	0.573	1
IO→KG	0.244	1
IUVI→KI	0.395	1
EIKF→KI	0.334	2
IUVI→KE	0.324	1

Table 6-20: The Relative Importance Ranking for the Negative Factors

	Relative Importance (-)	Rank
IIS→KA	-0.579	1
IO→KS	-0.333	1
LQI→KG	-0.419	1
IKI→KG	-0.27	2
IIS→KI	-0.274	1
LQI→KE	-0.438	1
IKI→KE	-0.386	2

Table 6-21 presents the total effects of sub factors within the positive driver constructs. The results show that the variable *Trustful Relationship with Business Partners* (TRP) and the variable *Information Accessibility* (ACCES) are the two most important positive variables for KA. As for KS, the variable *Data and Information Relevancy* (RELEV) is most important. Regarding KG, the impacts of the variables *Supplier Information Overload* (SIO), *Market Information Overload* (MIO) and *Internal Legacy Information Overload* (ILIO) are equal. As for KI, ACCES and the variable *Trustful Environment within Organization* (TEO) have the biggest positive impact. Finally, the variable information *Timeliness and Accuracy* (T&A) is the biggest positive influence factor for KE. **Table 6-22** presents the total effects of sub factors of the negative driver constructs. As for KA, the variable *Lack of Extended Enterprise Functionality* (LEEF) has the strongest total effect among the four sub factors within inappropriate information system (IIS). Regarding KS, total effects of MIO, SIO and ILIO are very similar. Moreover, the variables *Low Quality Downstream Information* (LQDI) and *Low Quality Upstream Information* (LQUI) are the two strongest negative sub factors for both KG and KE. Lastly, with respect to KI, the variable *Incompatibility of IT Systems* (INCOMPA) has the strongest effect.

Table 6-21: The Total Effects Ranking for the Positive First Order Factors

Second-Order	First-Order	Total Effect to KA	Rank
	TRP	0.101	1
EIKF	ECC	0.063	3
	TEO	0.06	4
	SL	0.001	8
	ACCES	0.08	2
IUVI	T&A	0.049	5
	RELEV	0.044	6
	SCAR	0.038	7
Second-Order	**First-Order**	**Total Effect to KS**	**Rank**
	RELEV	0.264	1
IUVI	T&A	0.163	2
	ACCES	0.146	3
	SCAR	0.127	4
Second-Order	**First-Order**	**Total Effect to KG**	**Rank**
	SIO	0.088	1
IO	MIO	0.087	2
	ILIO	0.086	3
Second-Order	**First-Order**	**Total Effect to KI**	**Rank**
	ACCES	0.182	1
IUVI	RELEV	0.112	3
	T&A	0.101	6
	SCAR	0.087	7
	TEO	0.175	2
EIKF	ECC	0.109	4
	SL	0.105	5
	TRP	0.002	8
Second-Order	**First-Order**	**Total Effect to KE**	**Rank**
	T&A	0.057	1
IUVI	SCAR	0.035	2
	RELEV	0.032	3
	ACCES	0.027	4

Table 6-22: The Total Effects Ranking for the Negative First Order Factors

Second-Order	First-Order	Total Effect to KA	Rank
	LEEF	-0.359	1
IIS	INFLEX	-0.07	2
	CM	-0.064	3
	INCOMPA	-0.062	4
Second-Order	**First-Order**	**Total Effect to KS**	**Rank**
	MIO	-0.12	1
IO	SIO	-0.101	2
	ILIO	-0.098	3
Second-Order	**First-Order**	**Total Effect to KG**	**Rank**
	LQDI	-0.219	1
LQI	LQUI	-0.213	2
	LIKI	-0.103	3
IKI	LEKI	-0.102	4
	LFKI	-0.077	5
Second-Order	**First-Order**	**Total Effect to KI**	**Rank**
	INCOMPA	-0.124	1
IIS	INFLEX	-0.075	2
	LEEF	-0.066	3
	CM	-0.03	4
Second-Order	**First-Order**	**Total Effect to KE**	**Rank**
	LQDI	-0.229	1
LQI	LQUI	-0.223	2
	LEKI	-0.147	3
IKI	LIKI	-0.147	3
	LFKI	-0.11	4

6.3 Multi-group Analysis

The focus of this section is to provide a comprehensive PLS-SEM multi-group analysis that complements the PLS-SEM structural model analysis presented in the previous sections of this chapter. The PLS structural model analysis usually analyses the full set of data, implicitly assuming that the data derive from a homogeneous population. In reality, however, it is not always the case. Respondents' backgrounds are frequently different (e.g. different countries, different industries, or different companies with different sizes, etc), so pooling data across different groups of observations is likely to produce misleading results. Therefore, not considering the heterogeneity/diversity of the data set can be a threat to the validity of PLS-SEM results (Becker et al., 2013).

Consequently, in recent years, researchers are increasingly interested in identifying and understanding such diversity (Hair et al., 2018). A PLS-SEM multi-group analysis is typically applied when researchers want to explore differences that are derived from observable characteristics such as country of origin, industry, gender, company size, annual income, etc. In this regard, these observable characteristics can be considered as categorical moderator variables that influences the relationships in the PLS path model. Hence, the purpose of multi-group analysis is to examine the effect of this categorical moderator variable (Hair et al., 2018). The multi-group analysis of this study chooses: the country comparison between China and the USA, the manufacturing industry comparison between food and drink and machinery and electronics industry, as well as the company size comparison between small and medium enterprises (SMEs) and large enterprises. In order to conduct a thorough multi-group analysis, there are two main steps included which are *measurement model invariance assessment* and *PLS multi-group analysis* (Hair et al., 2018). They will be illustrated in detail in the following sections.

6.3.1 Testing Measurement Model Invariance

Measurement invariance is the primary concern before comparing groups of data. By establishing measurement invariance, researchers can confidently conclude that "*group differences in structural model estimates do not result from the distinctive content and/or meanings of the latent variables across groups"* (Hair et al., 2018, pp.139). Variations in the structural relationships between latent variables in different groups could derive from several reasons: a) respondents holding different cultural values who interpret a given question in a conceptually different manner; b) gender, ethnicity, or other individual differences that cause different respondses to questions in systematically different ways; c) respondents who use the pre-set options on a scale differently (e.g. tendency to choose or not to choose the extremes). Therefore, the measurement invariance test is to reduce measurement inconsistency between what is intended to be measured and what is actually measured (Hult et al., 2008). When measure invariance is not established, it can influence the precision of estimators, and consequently reduce the credibility of the results.

Scholars have developed a variety of methods to assess measurement invariance for CB-SEM. The most common approach by far is multi-group confirmatory factor analysis that was developed based on the guidelines of Steenkamp and Baumgartner (1998) and Vandenberg and Lance (2000). However, these well-established methods and related extensions to formative measurement models developed by Diamantopoulos and Papadopoulos (2010) are incompatible with PLS-SEM's composite models. For this reason, Henseler et al., 2016) developed the "*measurement invariance of composite models (MICOM)* procedure that builds on the scores of the latent variables. *In PLS-SEM, these latent variables are represented as composites, that is, linear combinations of indicators and the indicator weights as estimated by the PLS-SEM algorithm"* (Hair et al., 2018, pp.140). The MICOM procedure consists of three steps: (1) configural invariance, (2) compositional invariance, and (3) equality of composite mean values and variances. These three steps are hierarchically interrelated, which means that configural invariance is a precondition for compositional invariance, which is again a precondition of valid assessment of the equality of composite mean values and variances (Hair et al., 2018).

Step 1: configural invariance

The purpose of this step is to ensure that each latent variable in the PLS path model has been specified equally for all the groups. "*Configural invariance exists when constructs are equally parameterized and estimated across groups"* (Hair et al., 2018, pp.142). In order to establish the latent variables' configural invariance, the following three requirements must be met:

1) *Identical indicators per measurement model*. It means that each measurement model must use the same indicators and scale across all groups. Using exactly the same indicators to all groups seems rather simple. However, when conducting a survey using different languages, it is crucial to have good translation techniques (e.g. back translation) for establishing the indicators' equivalence. In this context, pilot test or expert validity can help to check whether the researcher used the same

set of indicators across the groups.

2) *Identical data treatment*. It means that the indicators' data treatment must be the same across all the groups, which includes different kinds of coding techniques and the data handling (e.g. missing value treatment and outliers' detection and treatment).
3) *Identical algorithm setting or optimisation criteria*. PLS-SEM like many other variance-based model estimation methods consists of many variants with different target functions and algorithm settings (e.g. choice of initial outer weights and the inner model weighting scheme). Researchers should be careful when choose appropriate algorithm settings (Hair et al., 2018).

As for the present research, the languages used in the survey questionnaire are Chinese and English. In order to ensure that the questions or indicators have the same meaning to all respondents in both language environments, the researcher has followed the back translation procedure with native speaker translators in the UK and China to translate the questionnaire into these two languages. Later, the questionnaire has been checked and revised several times with the researcher's supervision team, colleagues and manufacturing industry practitioners. The details of pilot test and translation procedure have been discussed in the Chapter 5. Moreover, the PLS path model as well as the data treatment used in all groups are identical, which is a necessary requirement for the establishment of configural invariance in Step 1 of the MICOM procedure. Furthermore, the group-specific model estimations also draw on the identical algorithm settings. Hence, Step 1: configural invariance is established. However, it is not a sufficient condition for conducting multi-group analyses. Researchers also need to ensure that differences in multi-group analyses do not result from differences in the way a latent variable is formed across the groups (Hair et al., 2018). The next step: compositional invariance will focus on this aspect.

Step 2: compositional invariance

"Compositional invariance exists when the composite scores are the same across the groups, despite possible differences in the group-specific weights

used to compute the scores" (Hair et al., 2018, pp.143). The purpose of Step 2 is to employ a statistical test assessing whether the composite scores differ significantly across the groups. For this purpose, this step examines *c*, which is the correlation between the composite scores $Y^{(1)}$ and $Y^{(2)}$: $c = cor\ (Y^{(1)}, Y^{(2)})$. Note: the index $^{(1)}$ and $^{(2)}$ represent group 1 and group 2, respectively. In order to establish compositional invariance, it requires that c equals 1, and p value should be larger than 0.05 (at a significance level of 5%) (Hair et al., 2018). If $c \leq 1$ and p value is less than 0.05, it indicates that the correlation *c* is significantly lower than 1 and the compositional invariance is not established across the groups. For the testing, the MICOM procedure draws on the concept of permutation. A permutation test is an approach that randomly exchanges observations between the groups multiple times for calculating correlations between the composite scores of group 1 and 2 (Fisher, 1935).

Table 6-23, **Table 6-24** and **Table 6-25** present the results of compositional invariance testing for the three pairs of groups (i.e. China vs. the USA; SMEs vs. large business; and food and drink vs. machinery and electronics manufacturing). The column 5% shows the 5% quantile of the empirical distribution of c_u. It is the lower boundary of permutation-based confidence interval (i.e. the 950th of 1,000th permutations in the sorted list). Comparing the correlations *c* between the composite scores of the three pairs of groups with the 5% quantile reveals that the correlation *c* is always larger than (or equal to) the quantile for all the constructs. This result is also supported by the p values that are higher than 0.05, indicating the correlation is not significantly lower than 1. Therefore, compositional invariance of this research has been established. The assessment should continue with the equality assessment of the composites' mean values and variances.

Table 6-23: Compositional Invariance between Countries

Composite	Correlation *c*	5.00%	p-values	Compositional Invariance Established?
EIKF	0.985	0.911	0.836	Yes
IIS	0.979	0.933	0.624	Yes
IKI	1	0.998	0.8	Yes
IO	0.961	0.938	0.277	Yes
IUVI	1	1	0.548	Yes
KA	0.998	0.991	0.112	Yes
KE	1	0.998	0.35	Yes
KG	0.973	0.962	0.251	Yes
KI	0.968	0.947	0.733	Yes
KS	0.993	0.946	0.575	Yes
LQI	1	0.989	0.559	Yes

Table 6-24: Compositional Invariance between Industries

Composite	Correlation *c*	5.00%	p-values	Compositional invariance established?
EIKF	0.992	0.968	0.534	Yes
IIS	0.986	0.958	0.437	Yes
IKI	0.999	0.989	0.32	Yes
IO	0.991	0.976	0.512	Yes
IUVI	0.982	0.965	0.433	Yes
KA	1	0.998	0.434	Yes
KE	0.977	0.943	0.08	Yes
KG	0.985	0.951	0.532	Yes
KI	1	0.996	0.356	Yes
KS	0.966	0.959	0.525	Yes
LQI	0.997	0.974	0.159	Yes

Table 6-25: Compositional Invariance between Business Sizes

Composite	Correlation *c*	5.00%	p-values	Compositional Invariance established?
EIKF	1	1	0.118	Yes
IIS	0.997	0.987	0.234	Yes
IKI	0.98	0.968	0.432	Yes
IO	0.996	0.957	0.533	Yes
IUVI	1	0.992	0.548	Yes
KA	0.998	0.997	0.112	Yes
KE	0.982	0.967	0.633	Yes
KG	0.974	0.971	0.742	Yes
KI	0.979	0.977	0.17	Yes
KS	0.998	0.986	0.359	Yes
LQI	0.966	0.933	0.612	Yes

Step 3: equality of composite mean values and variances

This final step of the MICOM procedure first needs to use the pooled data (i.e.

the entire data set) to estimate the PLS path model for obtaining the composite scores, instead of conducting separate, group-specific PLS-SEM estimations as was done in step 2. After that, the researcher examines whether the mean values and variances between the composite scores of the group 1 and group 2 are statistically different (Hair et al., 2018).

For the analysis of the mean values' equivalence, according to Hair et al (2018), the null hypothesis is:

$$H_0 = \bar{Y}^{(1)}_{pooled} - \bar{Y}^{(2)}_{pooled} = 0$$

The null hypothesis H_0 can be regarded as an accepted fact or "nothing has changed" (Lakin, 2011). In this research, it represents that the mean values of the composite scores of both groups are equivalent. It can be rejected by the alternative hypothesis H_1 which represents an opposite meaning of the H_0.

For the analysis of the equivalence of the variances, it requires determining the logarithm of the variance ratio of the composite scores of both groups. If the logarithm of this ratio is not significantly different from 0, it can be concluded that the variances are equal across groups. According to Hair et al (2018), the corresponding null hypothesis is:

$$H_0 : log\left(\frac{var\left(Y^{(1)}_{pooled}\right)}{var\left(Y^{(2)}_{pooled}\right)}\right) = log\left(var\left(Y^{(1)}_{pooled}\right)\right) - log\left(var\left(Y^{(2)}_{pooled}\right)\right) = 0$$

The testing of these two hypotheses also employees the permutation approach as in Step 2. The MICOM permutation randomly rearranges observations between the groups many times and generates the empirical distribution of the differences in mean values and logarithms of variances. The equality of composite mean values and variances are established when there are no significant differences in mean values and logarithms of variances across the groups. If this is the case, the permutation-based confidence intervals (at the 95% level) of the differences in mean values and logarithms of variances include the original differences in mean values and variances as obtained by the original model estimation. In contrast, if one of these differences is significant, measure invariance cannot be established (Hair et al., 2018).

Table 6-26, **Table 6-27**, and **Table 6-28** present the results of equality of composite mean values and variances testing for the three pairs of groups (i.e. China vs. the USA; SMEs vs. large business; and food and drink vs. machinery and electronics manufacturing). The first column of these three tables shows the mean differences and variances between the composite scores as resulting from the original model estimation. In the next column, there are two numbers in each cell, which shows the lower (2.5%) and upper (97.5%) boundaries of the 95% confidence interval of the scores' mean differences and variances. As can be seen, every confidence interval includes the original difference in mean values, indicating that there are no significant differences in the mean values of latent variables across the groups. The similar results are shown for the composite variances. Again, all the confidence intervals include the original value and all the p values are clearly larger than 0.05. It can be concluded that all the composite mean values and variances are equal, hence, full measurement invariance is established across all groups. In light of these results, the multi-group analysis can be continued.

Table 6-26: Equality of Composite Mean Values and Variances between Countries

Composite	Difference of the composite's mean value (=0)	95% confidence interval	p-values	Equal mean values?
EIKF	-0.06	[-0.206; 0.222]	0.501	Yes
IIS	0.086	[-0.234; 0.223]	0.423	Yes
IKI	0.043	[-0.219; 0.242]	0.611	Yes
IO	-0.022	[-0.202; 0.215]	0.785	Yes
IUVI	-0.01	[-0.213; 0.244]	0.635	Yes
KA	0.043	[-0.202; 0.259]	0.231	Yes
KE	0.055	[-0.231; 0.243]	0.413	Yes
KG	0.086	[-0.228; 0.236]	0.312	Yes
KI	-0.047	[-0.225; 0.234]	0.525	Yes
KS	-0.063	[-0.218; 0.212]	0.603	Yes
LQI	-0.032	[-0.229; 0.205]	0.321	Yes
Composite	Logarithm of the composite's variances ratio (=0)	95% confidence interval	p-values	Equal variances?
EIKF	0.231	[-0.303; 0.287]	0.858	Yes
IIS	0.131	[-0.21; 0.235]	0.793	Yes
IKI	-0.042	[-0.338; 0.301]	0.512	Yes
IO	-0.026	[-0.287; 0.253]	0.413	Yes
IUVI	0.105	[-0.303; 0.29]	0.531	Yes
KA	-0.182	[-0.233; 0.377]	0.666	Yes
KE	-0.042	[-0.211; 0.307]	0.782	Yes
KG	0.17	[-0.229; 0.21]	0.373	Yes
KI	0.221	[-0.331; 0.364]	0.505	Yes
KS	0.191	[-0.279; 0.261]	0.389	Yes
LQI	-0.131	[-0.292; 0.308]	0.203	Yes

Table 6-27: Equality of Composite Mean Values and Variances between Industries

Composite	Difference of the composite's mean value (=0)	95% confidence interval	p-values	Equal mean values?
EIKF	0.028	[-0.246; 0.233]	0.783	Yes
IIS	-0.07	[-0.244; 0.248]	0.981	Yes
IKI	0.097	[-0.205; 0.221]	0.178	Yes
IO	0.031	[-0.23; 0.225]	0.461	Yes
IUVI	0.077	[-0.238; 0.229]	0.383	Yes
KA	0.01	[-0.212; 0.266]	0.388	Yes
KE	-0.023	[-0.275; 0.231]	0.632	Yes
KG	-0.097	[-0.222; 0.202]	0.27	Yes
KI	0.031	[-0.236; 0.201]	0.582	Yes
KS	0.098	[-0.243; 0.27]	0.317	Yes
LQI	0.054	[-0.251; 0.241]	0.712	Yes
Composite	Logarithm of the composite's variances ratio (=0)	95% confidence interval	p-values	Equal variances?
EIKF	0.081	[-0.306; 0.277]	0.433	Yes
IIS	0.135	[-0.252; 0.249]	0.517	Yes
IKI	-0.156	[-0.243; 0.208]	0.586	Yes
IO	0.033	[-0.229; 0.206]	0.612	Yes
IUVI	0.082	[-0.328; 0.251]	0.451	Yes
KA	-0.152	[-0.272; 0.233]	0.672	Yes
KE	-0.158	[-0.331; 0.305]	0.314	Yes
KG	-0.202	[-0.241; 0.25]	0.231	Yes
KI	0.24	[-0.232; 0.341]	0.517	Yes
KS	0.105	[-0.252; 0.305]	0.675	Yes
LQI	0.07	[-0.273; 0.288]	0.512	Yes

Table 6-28: Equality of Composite Mean Values and Variances between Business Sizes

Composite	Difference of the composite's mean value (=0)	95% confidence interval	p-values	Equal mean values?
EIKF	0.027	[-0.221; 0.238]	0.335	Yes
IIS	0.064	[-0.215; 0.224]	0.412	Yes
IKI	0.051	[-0.236; 0.208]	0.123	Yes
IO	-0.071	[-0.212; 0,245]	0.441	Yes
IUVI	0.035	[-0.228; 0.231]	0.533	Yes
KA	0.051	[-0.234; 0.22]	0.612	Yes
KE	0.091	[-0.204; 0.211]	0.638	Yes
KG	0.083	[-0.235; 0.228]	0.278	Yes
KI	-0.059	[-0.237; 0.229]	0.243	Yes
KS	0.073	[-0.207; 0.213]	0.512	Yes
LQI	-0.044	[-0.205; 0.241]	0.732	Yes
Composite	Logarithm of the composite's variances ratio (=0)	95% confidence interval	p-values	Equal variances?
EIKF	0.23	[-0.372; 0.308]	0.312	Yes
IIS	0.177	[-0.238; 0.307]	0.562	Yes
IKI	0.221	[-0.289; 0.258]	0.187	Yes
IO	-0.102	[-0.244; 0.31]	0.322	Yes
IUVI	0.056	[-0.332; 0.312]	0.476	Yes
KA	0.173	[-0.307; 0.271]	0.631	Yes
KE	0.2	[-0.287; 0.259]	0.432	Yes
KG	-0.19	[-0.212; 0.298]	0.254	Yes
KI	-0.158	[-0.318; 0.265]	0.712	Yes
KS	-0.212	[-0.25; 0.267]	0.821	Yes
LQI	0.275	[-0.281; 0.321]	0.132	Yes

6.3.2 Multi-group Analysis

Using different samples to calculate the path coefficients in the same path model, the results are almost always numerically different, but the question is whether the differences are statistically significant. To answer this question is the purpose of multi-group analysis. "*Technically, a multi-group analysis tests the null hypotheses H_0 that the path coefficients between two groups (e.g. $p^{(1)}$ in group 1 and $p^{(2)}$ in group 2) are not significantly differently (e.g. $p^{(1)}=p^{(2)}$), which amounts to the same as saying that the absolute difference between the path coefficients is 0 (i.e. $H_0 : \left|p^{(1)} - p^{(2)}\right| = 0$). The corresponding alternative hypothesis H_1 is that the path coefficients are different (i.e. $H_1 : p^{(1)} \neq p^{(2)}$ or, put differently, $H_1 : \left|p^{(1)} - p^{(2)}\right| > 0$)"* (Hair et al., 2018, pp.148).

According to (Sarstedt, et al., 2011), there are three methods to comparing two groups of data in PLS-SEM, which are parametric test, PLS-MGA, and permutation test. The first two methods are recommended when one group's sample is more than double the size of the other groups'. However, for the present research, the group-specific sample sizes have no large differences. The largest difference in the sample size of this research comes from the group of business size comparison (i.e. 128 for SMEs, 231 for large companies). In addition, the parametric test and PLS-MGA have several drawbacks. For the parametric approach, it is rather liberal and likely suffer from Type I errors. A Type I error is also known as a false positive and occurs when a researcher incorrectly rejects a true null hypothesis (Sarstedt et al., 2011). Moreover, from a conceptual perspective, the parametric approach is inconsistent with PLS-SEM's nonparametric nature, since it relies on distributional assumptions (Hair et al., 2018). As for the PLS-MGA, it allows for testing only one-sided hypotheses. Therefore, using this approach to test two-sided hypotheses has limitations as the bootstrap-based distribution is not always symmetric. This characteristic would limit its applicability as researchers usually apply two-tailed tests (Hair et al., 2018). This research will adopt the permutation approach for conducting the multi-group analysis, since in general it has been shown to perform very well, especially in controlling for Type I errors when the rearrangement of observations occurs randomly between data groups, as is the case in the application of permutation test in PLS-SEM. Therefore, this approach performs more conservatively than the parametric test in terms of rendering differences significant (Sarstedt, et al., 2011).

The permutation test is similar to its role in Step 2 of the MICOM procedure. It randomly exchanges observations between the data groups and re-estimates the model for each permutation (Chin and Dibbern, 2010). Calculating the differences between the group-specific path coefficients each permutation enables testing whether these differences also exist in the full sample (Hair et al., 2018).

Table 6-29, **Table 6-30** and **Table 6-31** present the results of multi-group analysis for the three pairs of groups (i.e. China vs. the USA; SMEs vs. large business; and food and drink vs. machinery and electronics manufacturing).

The first two columns of these three tables show the original path coefficients in group 1 and group 2, respectively. Note that the index * and ** in these two columns represent $p < 0.05$ and $p < 0.01$ (i.e. at a significance level of 5% and 1%), respectively. If the path coefficient with a significance of p value less than 0.01 or 0.05, then the hypothesized relationship between constructs is supported by empirical data (Hair et al., 2017). In addition to that, the rest of the columns present the two groups' differences in the original data set and the permutation testing, respectively.

As shown in **Table 6-29**, all the structural model relationships do not differ significantly between China and the USA. The results of hypotheses testing are also the same as that of the aggregate-level path model analysis shown in **Figure 6-4**. Furthermore, in **Table 6-30**, most structural model relationships do not differ between SMEs and large enterprises. The only exceptions are the relationships between EIKF and KA, IIS and KG, as well as IUVI and KG. More specifically, the effect between EIKF and KA is significantly different ($p < 0.1$, at a significance level of 10%) between SMEs ($p^{(1)} = 0.166$) and large enterprises ($p^{(2)} = 0.353$). Similarly, the relationship between IIS and KG is significantly different ($p < 0.05$, at a significance level of 5%) between SMEs ($p^{(1)} = 0.027$) and large enterprises ($p^{(2)} = -0.195$). Moreover, the effect of IUVI on KG is significantly different ($p < 0.1$) among SMEs ($p^{(1)} = -0.017$) and large enterprises ($p^{(2)} = 0.181$). Lastly, based on the significance level index shown in the two original path coefficients columns, it can be seen that EIKF has a stronger effect on KA in large enterprises than it has in SMEs, besides, both IIS→IG and IUVI→KG are supported in large enterprises but not in SMEs. With respect to the results in **Table 6-31**, most structural model relationships do not differ significantly between food and drink industry and machinery and electronics manufacturing. However, the relationship between EIKF and KG, as well as the relationship between IUVI and KG are significantly different ($p < 0.1$) between food industry and machinery industry. In addition, as shown in the two original path coefficients columns, these two hypotheses are only supported in the context of machinery industry.

Table 6-29: Permutation Test for Country Comparison

	Path Coefficients Original (China)	Path Coefficients Original (USA)	Path Coefficients Original Difference (China - USA)
EIKF→KA	0.299**	0.172*	0.127
EIKF→KG	-0.033	-0.068	0.035
EIKF→KI	0.358**	0.259**	0.099
IIS→KA	-0.502**	-0.632*	0.13
IIS→KE	-0.035	0.018	-0.053
IIS→KG	-0.043	0.087	-0.13
IIS→KI	-0.412**	-0.263**	-0.149
IKI→KA	-0.012	0.031	-0.043
IKI→KE	-0.453**	-0.339**	-0.114
IKI→KG	-0.198**	-0.35**	0.152
IO→KG	0.228**	0.337**	-0.109
IO→KS	-0.296**	-0.441**	0.145
IUVI→KA	0.249*	0.153*	0.096
IUVI→KE	0.295**	0.363**	-0.068
IUVI→KG	0.02	0.006	0.014
IUVI→KI	0.46**	0.342**	0.118
IUVI→KS	0.438**	0.593**	-0.155
LQI→KE	-0.392**	-0.51**	0.118
LQI→KG	-0.489**	-0.376**	-0.113
	Path Coefficients Permutation Mean Difference (China - USA)	**95% Confidence Interval**	**Permutation p-Values**
EIKF→KA	0.005	[-0.213; 0.225]	0.235
EIKF→KG	-0.004	[-0.206; 0.211]	0.327
EIKF→KI	0.007	[-0.162; 0.155]	0.44
IIS→KA	-0.001	[-0.213; 0.226]	0.285
IIS→KE	0.001	[-0.201; 0.217]	0.316
IIS→KG	-0.003	[-0.241; 0.228]	0.371
IIS→KI	0.004	[-0.292; 0.281]	0.103
IKI→KA	-0.006	[-0.233; 0.217]	0.333
IKI→KE	0.005	[-0.208; 0.206]	0.292
IKI→KG	0.002	[-0.257; 0.247]	0.116
IO→KG	-0.008	[-0.197; 0.208]	0.103
IO→KS	0.002	[-0.242; 0.258]	0.212
IUVI→KA	0.004	[-0.257; 0.263]	0.364
IUVI→KE	0.006	[-0.181; 0.176]	0.337
IUVI→KG	-0.003	[-0.151; 0.156]	0.466
IUVI→KI	0.006	[-0.285; 0.278]	0.228
IUVI→KS	0.002	[-0.259; 0.241]	0.112
LQI→KE	-0.001	[-0.203; 0.221]	0.253
LQI→KG	0.004	[-0.237; 0.229]	0.287

Table 6-30: Permutation Test for Business Size Comparison

	Path Coefficients Original (SMEs)	Path Coefficients Original (Large)	Path Coefficients Original Difference (SMEs - Large)
EIKF→KA	0.166**	0.353**	-0.187
EIKF→KG	-0.082	-0.043	-0.039
EIKF→KI	0.301**	0.422**	-0.121
IIS→KA	-0.517**	-0.6**	0.083
IIS→KE	-0.028	0.015	-0.043
IIS→KG	0.027	-0.195**	0.222
IIS→KI	-0.177*	-0.311**	0.134
IKI→KA	0.012	0.044	-0.032
IKI→KE	-0.407**	-0.297**	-0.11
IKI→KG	-0.182*	-0.314**	0.132
IO→KG	0.32**	0.207**	0.113
IO→KS	-0.285**	-0.353**	0.068
IUVI→KA	0.163*	0.232**	-0.069
IUVI→KE	0.258**	0.361**	-0.103
IUVI→KG	-0.017	0.181**	-0.198
IUVI→KI	0.479**	0.35**	0.129
IUVI→KS	0.623**	0.497**	0.126
LQI→KE	-0.368**	-0.479**	0.111
LQI→KG	-0.377**	-0.504**	0.127
	Path Coefficients Permutation Mean Difference (SMEs - Large)	95% Confidence Interval	Permutation p-Values
EIKF→KA	-0.003	[-0.201; 0.212]	0.064
EIKF→KG	0.002	[-0.177; 0.173]	0.365
EIKF→KI	0.005	[-0.291; 0.279]	0.279
IIS→KA	0.007	[-0.257; 0.261]	0.413
IIS→KE	-0.001	[-0.246; 0.272]	0.451
IIS→KG	-0.002	[-0.209; 0.215]	0.036
IIS→KI	0.007	[-0.229; 0.221]	0.215
IKI→KA	0.003	[-0.172; 0.156]	0.42
IKI→KE	-0.004	[-0.255; 0.263]	0.451
IKI→KG	0.006	[-0.261; 0.249]	0.151
IO→KG	0.007	[-0.233; 0.227]	0.168
IO→KS	0.003	[-0.209; 0.197]	0.571
IUVI→KA	0.008	[-0.171; 0.190]	0.286
IUVI→KE	-0.005	[-0.276; 0.285]	0.151
IUVI→KG	0.002	[-0.297; 0.302]	0.076
IUVI→KI	0.004	[-0.251; 0.243]	0.117
IUVI→KS	0.002	[-0.236; 0.232]	0.106
LQI→KE	0.001	[-0.279; 0.265]	0.235
LQI→KG	0.007	[-0.251; 0.266]	0.373

Table 6-31: Permutation Test for Industry Comparison

	Path Coefficients Original (Food)	Path Coefficients Original (Machinery)	Path Coefficients Original Difference (F - M)
EIKF→KA	0.159*	0.265**	-0.106
EIKF→KG	-0.086	0.153*	-0.239
EIKF→KI	0.288**	0.409**	-0.121
IIS→KA	-0.463**	-0.597**	0.134
IIS→KE	-0.033	-0.01	-0.023
IIS→KG	-0.006	-0.021	0.015
IIS→KI	-0.351**	-0.216**	-0.135
IKI→KA	0.016	0.041	-0.025
IKI→KE	-0.277**	-0.416**	0.139
IKI→KG	-0.21**	-0.303**	0.093
IO→KG	0.222**	0.343**	-0.121
IO→KS	-0.312**	-0.396**	0.084
IUVI→KA	0.152*	0.218**	-0.066
IUVI→KE	0.289**	0.411**	-0.122
IUVI→KG	0.002	0.167*	-0.165
IUVI→KI	0.353**	0.447**	-0.094
IUVI→KS	0.603**	0.489**	0.114
LQI→KE	-0.386**	-0.521**	0.135
LQI→KG	-0.382**	-0.467**	0.085

	Path Coefficients Permutation Mean Difference (F - M)	95% Confidence Interval	Permutation p-Values
EIKF→KA	0.005	[-0.245; 0.252]	0.256
EIKF→KG	0.002	[-0.225; 0.218]	0.036
EIKF→KI	0.007	[-0.237; 0.231]	0.351
IIS→KA	0.004	[-0.271; 0.265]	0.412
IIS→KE	-0.001	[-0.143; 0.157]	0.277
IIS→KG	0.005	[-0.171; 0.153]	0.319
IIS→KI	-0.007	[-0.215; 0.222]	0.457
IKI→KA	0.008	[-0.217; 0.215]	0.533
IKI→KE	0.004	[-0.243; 0.257]	0.132
IKI→KG	-0.002	[-0.173; 0.188]	0.365
IO→KG	0.004	[-0.285; 0.281]	0.287
IO→KS	-0.001	[-0.191; 0.205]	0.446
IUVI→KA	0.006	[-0.261; 0.252]	0.396
IUVI→KE	-0.003	[-0.237; 0.251]	0.213
IUVI→KG	0.007	[-0.201; 0.211]	0.091
IUVI→KI	-0.004	[-0.167; 0.181]	0.163
IUVI→KS	-0.002	[-0.295; 0.301]	0.175
LQI→KE	0.003	[-0.287; 0.278]	0.246
LQI→KG	0.001	[-0.219; 0.205]	0.368

6.4 Summary

This chapter was dedicated to data analysis and hypotheses testing for this research. It is comprised of three main sections. In section 6.1, the quality of the full dataset has been assessed, which includes the sample characteristics, missing data, suspicious response patterns, outliners, and data distributions.

In section 6.2, a series of aggregate-level analyses was conducted in order to test the hypotheses presented in Chapter 2 and examine the structural model's predictive capabilities. **Table 6-32** recalled and summarised the testing results of the hypotheses. Firstly, in the four lean wastes, it was revealed that the *Inappropriate Information System* (IIS) has no impact on the *Knowledge Generation* (KG) and *Knowledge Externalisation* (KE), and *Insufficient Knowledge Inventory* (IKI) has no impact on Knowledge Acquisition (KA). A more interesting finding is that *Information Overload* (IO) has a positive and statistically significant impact on *Knowledge Generation* (KG), which is contrary to theoretical expectation. Hence, the hypotheses H1b, H1d, H1f and H1i were rejected. Secondly, in the hypotheses set of two lean principles, it was found that both *Identification and Usage of Valuable Information and Knowledge* (IUVI) and *Encouraging Information and Knowledge Flow* (EIKF) have no significant impact on *Knowledge Generation* (KG). Hence, H2c and H2g were rejected.

With respect to section 6.3, the purpose of this section was to conduct a multi-group analysis in order to explore whether there is any difference when the theoretical model is applied in different contexts (i.e. China vs. the USA, SMEs vs. large enterprises, food and drink industry vs. machinery and electronics manufacturing). As can be seen from **Table 6-32**, all the structural model relationships are very similar statistically in country comparison. In the industry comparison, two hypotheses: H2g. EIKF→KG and H2c. IUVI→KG are only supported in the context of machinery and electronics manufacturing. In the business size comparison, H2f. EIKF→KA is supported in the context of both SEMs and large enterprises. However, the effect of EIKF on KA is stronger in large size businesses than that in SMEs. Moreover, H1d. IIS→KG and H2c.

IUVI→KG are only supported in large enterprises. The rest of the hypothesis testing results in multi-group analysis are similar to the results in aggregate-level structural model analysis.

Table 6-32: Comparative Results of Hypothesis Testing

Hypothesis	Lean-KPPs	China	UK	Food & Drink	Machinery & Electronics	SMEs	Large
H1. Lean wastes have negative impact on knowledge product processes							
H1a. Information overload has a negative impact on knowledge selection	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1b. Information overload has a negative impact on knowledge generation	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported
H1c. Inappropriate information system has a negative impact on knowledge acquisition	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1d. Inappropriate information system has a negative impact on knowlegde generation	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported	Yes
H1e. Inappropriate information system has a negative impact on knowledge internalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1f. Inappropriate information system has a negative impact on knowlegde externalisation	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported
H1g. Low quality information has a negative impact on knowledge generation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1h. Low quality information has a negative impact on knowledge externalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1i. Insufficient knowledge inventory has a negative impact on knowledge acquisition	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported	Not supported
H1j. Insufficient knowledge inventory has a negative impact on knowledge generation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H1k. Insufficient knowledge inventory has a negative impact on knowlegde externalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2. Lean principles have positive impact on knowledge product processes							
H2a. Identification & usage of valuable information and knowledge has a positive impact on knowledge	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2b. Identification & usage of valuable information and knowledge has a positive impact on knowledge selection	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2c. Identification & usage of valuable information and knowledge has a positive impact on knowledge generation	Not supported	Not supported	Not supported	Not supported	Yes	Not supported	Yes
H2d. Identification & usage of valuable information and knowledge has a positive impact on knowledge internalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2e. Identification & usage of valuable information and knowledge has a positive impact on knowlegde externalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2f. Encouraging information and knowledge flow has a positive impact on knowledge acquisition	Yes	Yes	Yes	Yes	Yes	Yes	Yes
H2g. Encouraging information and knowledge flow has a positive impact on knowledge generation	Not supported	Not supported	Not supported	Not supported	Yes	Not supported	Not supported
H2h. Encouraging information and knowledge flow has a positive impact on knowledge internalisation	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 7 Discussion

This chapter discusses the results reported in Chapter 6, which are jointly discussed and linked to the proposed research questions in Chapter 1. These findings are compared to the conceptual model and the literature in order to discuss and explain any differences. The chapter starts by briefly recalling the *research gaps* along with *the research model* and the *research questions*. The next section explains the research findings, and finally these are assessed against the literature.

7.1 The Research Gaps, Model and Research Questions

Despite the fact that the concept of Lean thinking has been the subject of several studies on increasing KM level (Staats, et al., 2011; Yusof, et al., 2012; Sloan et al., 2014; Amrit et al., 2015; Zhao et al., 2016), the review of literature (in section 2.1.3 and 2.1.4) revealed that most of these works mainly focused on service or high-tech industries, with very few studies were carried out in manufacturing industries. This is surprising given the fact that the Lean thinking was derived from the manufacturing sector. Consequently, there are no tailored Lean-KM practices (i.e. Wastes and Principles) for manufacturing industries to improve their KM performance. Moreover, the review also revealed the lack of an overall approach for improving KM. The majority of the studies only focused on either knowledge sharing or knowledge innovation. Besides, Gupta et al. (2016) also made a call for more rigorous industry-specific empirical studies as most of these works are company or project-specific with a case study approach.

Therefore, in an attempt to address the abovementioned shortcomings in the prior studies, the present research has developed a conceptual model with three key components, namely, Lean-KM Wastes, Lean-KM Principles and KMPs, as shown **Figure 3-1**. Along with the conceptual model, six research questions were developed and detailed in Chapter 1. This chapter links the study's findings to the research questions. Research questions 1, 2, and 3 were addressed in the literature review and model development process in Chapter 2 and Chapter 3, respectively. In addition, the constructs of *Lean-KM Wastes*, *Lean-KM Principles*, and *KMPs* were operationalised in these two chapters. Then, the research questions 4 and 5 were addressed in Chapter 6 by using structural model analysis. Research question 6 has been answered in the last section of this chapter via multi-group analysis: Country China vs. the US, Industry machinery and electronics manufacturing vs. food and drink, Business size SMEs vs. large companies. In order to answer these two research questions, two main hypotheses were proposed in this study:

Hypothesis 1: Lean-KM Wastes has negative impact on KMPs.

Hypothesis 2: Lean-KM Principles has positive impact on KMPs.

Each main hypothesis consists of several sub-hypotheses so as to accurately measure to what extent the Lean-KM Wastes and Lean-KM Principles could affect manufacturing supply chain's KMPs. Under hypothesis 1, there are 11 sub-hypotheses (i.e. H1a, H1b, H1c, H1d, H1e, H1f, H1g, H1h, H1i, H1j, and H1k). Hypothesis 2 is measured 8 sub-hypotheses (i.e. H2a, H2b, H2c, H2d, H2e, H2f, H2g, and H2h). All research hypotheses were empirically tested in Chapter 6.

All sub-hypotheses and the research findings are presented in **Figure 7-1** and **Figure 7-2**. In these two figures, the blue arrows indicate that the hypothesis is supported, red arrows supported only under certain circumstance, and black dotted arrows indicate that the hypothesis is rejected. In the following sections, the research findings are discussed in-depth based on each of the research questions and hypotheses mentioned above.

Figure 7-1: Relations between Lean-KM Wastes and KMPs, Sub-Hypotheses Testing Results

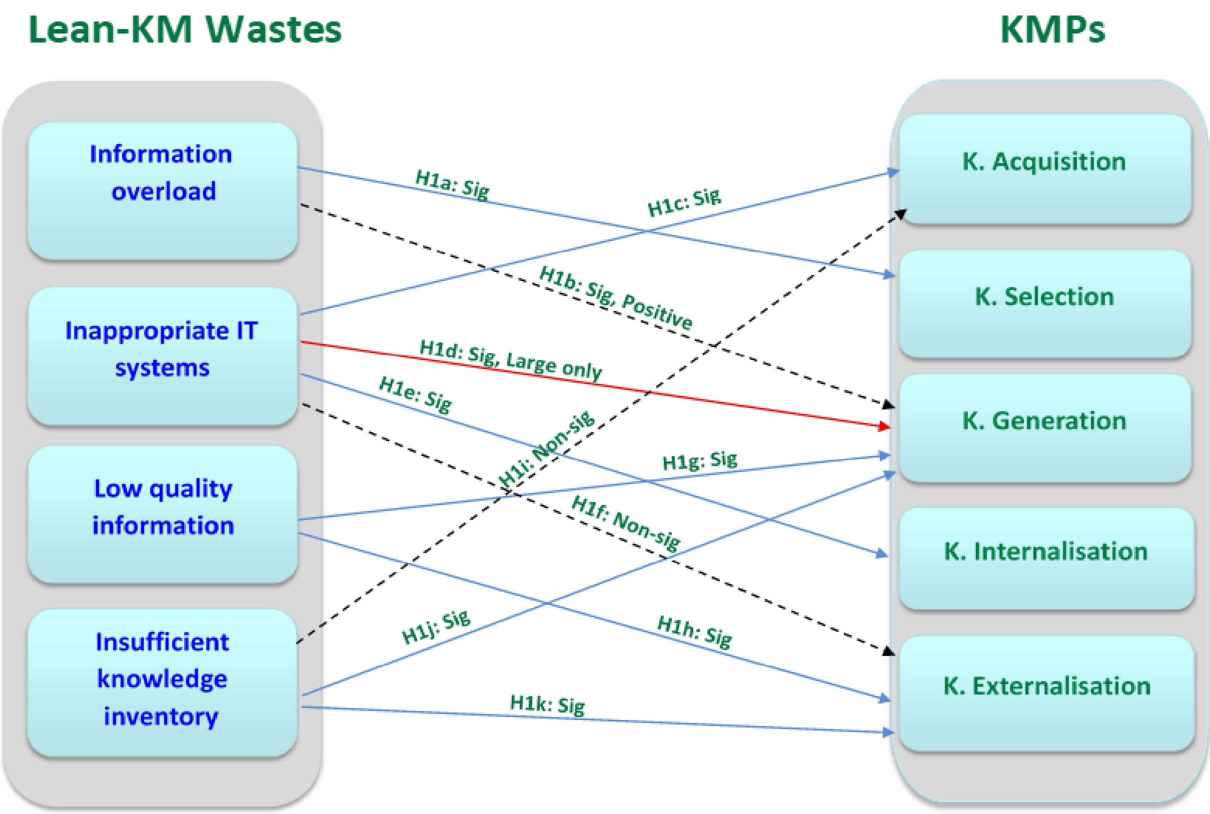
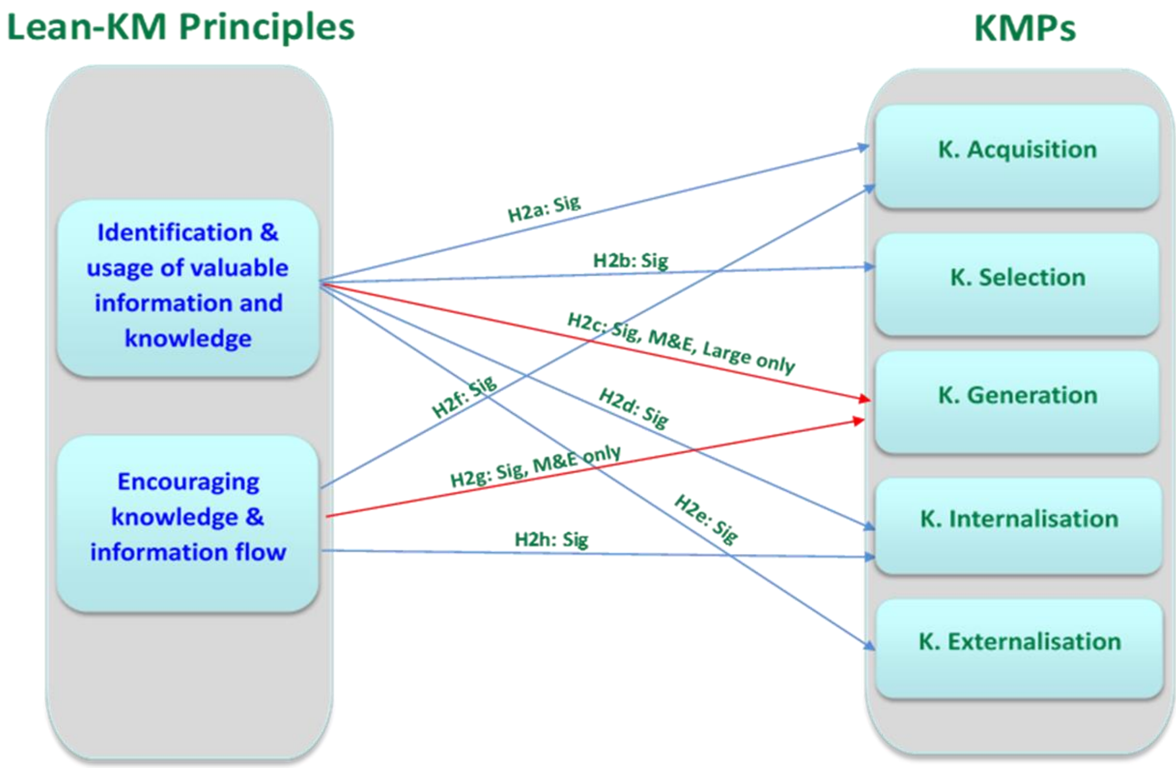


Figure 7-2: Relations between Lean-KM Principles and KMPs, Sub-Hypotheses Testing Results



7.2 Discussion on Research Findings

7.2.1 Answering Research Question 1: What Are the Major Dimensions or Activities of KM in the Manufacturing Supply Chain Context?

Identifying and delivering value to the end-customers or users is important to organisational success. This value, among others, is created or derived from knowledge assets within organisations. These assets and their effective application are critical for organisation success and act as a differentiating competitive factor (Dehnavi, 2015). In the manufacturing supply chain context, there are mainly two types of knowledge: internal and external. Internal knowledge consists of the information and knowledge needed for solving issues inside the company in operation or production related tasks. External knowledge includes the information and knowledge necessary for solving issues in supply chain partner relationships, and dealing with changes, threats and risks from the outside environment of the company. Management of these knowledge assets is known as KM.

KM is defined as a systematic approach to manage the use of information in order to provide a continuous knowledge flow to the right people at the right time enabling efficient and effective decision making in their everyday business (Payne and Britton, 2010). Through KM an organisation's intangible assets can be better utilised to create value, with both internal and external knowledge being leveraged to the benefit of the whole supply chain.

Knowledge management process, also known as knowledge chain or knowledge spiral, is the embodiment of knowledge management. It is a systematic process comprised of five activities including:

1) **Knowledge acquisition** means that organisations identify necessary knowledge from external environment and transform it into a form which can be used to generate new knowledge. Examples of knowledge acquisition include conducing an external survey, getting information and technical support from supply chain partners, sending employees to external training, purchasing data sets and patented processes, and gathering knowledge via competitive intelligence (Holsapple and Singh, 2001).
2) **Knowledge selection** means that organisations identify needed knowledge within its existing knowledge resources and provide the knowledge in a right form to an activity that needs it. Examples of knowledge selection in the manufacturing context include selecting qualified employees to participate in a product development team, selecting an appropriate procedure for forecasting, extracting needed information from a repository database, or field observation in an organisation (Holsapple and Singh, 2001).
3) **Knowledge generation** is an activity that organisation create knowledge by discovering it or deriving it from existing knowledge (Holsapple and Singh, 2001; Daud and Yusuf, 2008). Examples of knowledge generation include developing products and services, deriving demand forecasts, making decisions, plans and strategies,

recognising or solving problems, inventing managerial practices and technological processes (Holsapple and Singh, 2001; Nonaka, 2007).

4) **Knowledge internalisation** is an activity that alters an organisation's knowledge resources in order to refine and update its own knowledge repository. Examples of this activity include knowledge sharing, in-house training, populating a data warehouse, posting an idea on an intranet, publishing a policy manual, broadcasting a new regulation, and modifying organisational culture or infrastructure, making experts' knowledge available by developing expert systems (Holsapple and Singh, 2001).
5) **Knowledge externalisation** refers to using existing knowledge to produce organisational output for release into the environment. It transforms raw materials into products and services for external consumption. Examples of externalisation also include developing an advertisement and publishing a report.

7.2.2 Answering Research Question 2 and 3: What Are the Lean Wastes and Lean Principles That Could Affect Supply Chain KMPs?

The aim of Lean thinking is to eliminate wastes in all aspect of a business. By mapping process through the operation, it is possible to sort value adding and non-value-adding activities. Non-value-adding activities are wastes which should be improved or cut off from the process. Lean thinking was initially applied in the automotive manufacturing sector. However, since then many other industries have implemented its principles as they also wished to profit from its benefits.

Due to the similarity between the KM value flow model and the manufacturing system value flow model (discussed in section 2.4.3), Lean thinking can be applied in KM. Over the past 10 years, several researchers have identified a variety of wastes existing in KM system based on their own implementation context. In this research, by summarising and synthesising the common features of these wastes which include: 1) excessive information and documentation; 2) lack of necessary information and knowledge; 3) inappropriate data and information processing system; 4) inaccurate data and information, four Lean-KM Wastes have been developed in accordance with the context of manufacturing supply chain. Each Lean-KM Wastes contains two to four first order components in order to accurately and comprehensively measure their impacts on manufacturing supply chain's KMPs in Chapter 6. The four Lean-KM Wastes and their first order components include:

1) **Information overload** can be defined as the point where there is too much information that exceeds the users' information processing capacity for completing their tasks. It could make decision makers not be able to locate the most relevant information or knowledge, which in turn prolongs the decision time and reduces the decision quality. In the context of manufacturing supply chain, there are three types of information overload:
   --Supplier information overload
   --Market information overload
   --Internal legacy information overload
2) **Low quality information** refers to the information which is inaccurate, not east to access, unreliable, and delivered untimely. In supply chain context, sharing and using low quality information could damage the collaboration and KM performance among supply chain members. Due to the bidirectional nature of information flow in a supply chain, low quality information includes:
   --Low quality downstream information
   --Low quality upstream information
3) **Inappropriate information system**: In the past two decades, IT systems, especially ERP systems, have played an important role in supply chain management of manufacturing industries. It integrates all aspects of a supply chain, such as order processing, purchasing and production planning, logistics, and so on. The data and information generated from these aspects is stored, processed and delivered seamlessly across the relevant members. However, using a faulty developed IT system would damage a supply chain's performance. In

this research, four malfunctions of ERP systems have been identified through reviewing the previous literatures, which are:

--Incompatibility

--Lack of extended enterprise function

--Inflexibility

--Culture and content mismatch

4) **Insufficient knowledge inventory**: Knowledge inventory or repository is organisational experience and capabilities for knowledge users to store and reuse for their decision making in the future. Insufficient knowledge inventory leads to an organisation wasting their effort and time to acquire or rediscover the critical information and knowledge for completing their tasks. There are three types of knowledge inventories, lack of any of them would negatively impact a supply chain's KM performance. They include:

   --Lack of interactional knowledge inventory

   --Lack of functional knowledge inventory

   --Lack of environmental knowledge inventory

With respect of Lean-KM Principles, it can be regarded as a guidance for the implementation of Lean thinking in supply chain KM. Inspired Womack and Jones (1996) and Hicks (2007)'s the Lean Principles, this research developed two Lean-KM Principles based on the context of manufacturing supply chain, each of them is consisted of four first order components, which are:

1) **Identification and usage of valuable information and knowledge**: Identifying value and then adding value to the product or service for customers in a value stream is the critical starting point of Lean Principle. From the KM perspective, one of the most important functions of KM is to identify and recognise value-adding processors and knowledge resources so as to make sure every phase in the knowledge chain provides specific knowledge resources which meet the knowledge user's requirements at the right form, the right time, and the right cost (Holsapple and Singh, 2001). Hence, it corresponds to the Lean Principle. In terms of valuable information and knowledge in the supply

chain context, by summarising the definitions provided in prior studies, this research defines information value from four aspects:

--Relevancy

--Timeliness and accuracy

--Scarcity

--Accessibility

2) **Encouraging information and knowledge flow**: The purpose of this Lean Principle is to ensure that knowledge flows efficiently and only the most valuable knowledge is allowed to flow among the supply chain members (Hicks, 2007). In order to achieve this, there are four factors developed in this research, including:

--Trustful environment within organisation

--Trustful relationship with business partners

--Shared language

--Expanding communication channel

7.2.3 The Results from Hypotheses Testing: Answering Research Question 4, 5 and 6

As for research 4, 5 and 6, those relationships were empirically examined in Chapter 6. The findings are presented in this section.

Impact of Lean-KM Wastes on KMPs: Answering Research Question 4

H1a and H1b: Information overload (IO) has negative impacts on knowledge selection (KS) and knowledge generation (KG)

The hypothesis H1a was supported in this research, as the path model analysis indicated that IO has a negative impact on KS. The level of impact was revealed to be moderate and statistically significant at a 5% level. The result suggested that gathering too much information can significantly constrain the ability of an organisations to identify and select the critical information or knowledge for completing their tasks. Apart from the path model analysis, this study also conducted a further analysis which includes ranking the second order constructs' relative importance and their sub-factors' the total effects. The former is to find out which independent latent construct has the strongest impact on a certain dependent variable. The latter is to identify the strongest first order driver construct (i.e. the sub-factor of an independent second order construct) on the target variables. These two types of analyses are important to managerial implication. Since IO is the only factor that brings negative impact on KS in the Lean-KMPs model, its relative importance cannot be ranked with those of others. The total effects of IO's sub-components: *Market Information Overload* (MIO), *Supplier Information Overload* (SIO), and *Internal Legacy Information Overload* (ILIO), are very similar. Therefore, this result implies that manufacturing companies should avoid all these three sub-dimensions of IO at the same time for improving their KS performance.

The hypothesis H1b was not supported. However, result showed that the path coefficient between IO and KG is positive at a significant level of 1%. Their coefficient of determination is substantial. It implies that in order to improve KG performance (e.g. product design, decision and strategy making, and problem solving), a company should gather as much relevant information or knowledge as they can. In addition, since IO is the only factor that brings positive impact on KG in the Lean-KMPs model, and the total effect of its three sub-components: SIO, MIO, and ILIO, are very close. Hence, it is advisable for companies to cover all three sub-components at the same time for improving KG performance.

Many studies have claimed that information overload can undermine companies' decision making (KG) performance. However, most of them forgot that IO is a subjective feel of human beings. It is impossible to find a universal threshold of information to make everyone overloaded since information processing ability varies from person to person (Chen et al., 2009). Human decision making actually is a complex dynamic process which is deeply influenced by a person's experiences. Thus, the same set of information can be perceived by an experienced decision maker as a useful and abundant resource, whilst for a novice it would be an information overload (Zhang et al., 2018). Although it is often difficult to obtain useful and relevant information among the vast volumes of information, this has been proven in this research, with the help of modern information technologies (e.g. big data, cloud computing, and blockchain) for searching, accessing and retrieving information, companies today want to acquire business information as comprehensive as possible in order to make accurate plans and decisions, monitor the business process, identify risks where the process fails and take effective actions. A lack of information will lead to various problems (Gong et al., 2014). Therefore, the information must be acquired and transferred completely, quickly and accurately to guarantee quality decision making. Such large amount of information may make some employees feel overwhelmed. However, based on the result of this research and abovementioned reasons it is too bold to make a statement that information overload leads to bad quality decision making.

H1c, H1d, H1e and H1f: Inappropriate information system (IIS) has negative impacts on knowledge acquisition (KA), KG, knowledge internalisation (KI), and knowledge externalisation (KE)

The proposed association from IIS to KA was found to be significant. Therefore, the proposed hypothesis H1c was supported, implying that companies' ability of acquiring necessary information or knowledge can be significant inhibited by badly designed information system. Moreover, IIS is the only factor that has a negative impact on KA in the Lean-KMPs model, the sub-component *Lack of Extended Enterprise Function* (LEEF) has the largest total effect to KA among other sub-components of IIS: *Inflexibility* (INFLEX), *Cultural Misfits* (CM), and Incompatibility (INCOMPA). Therefore, it is advisable for manufacturing companies to focus on integrating their IT system, especially ERP system, with those of their business partners in order to acquire necessary information at the right form, the right time, and the right cost.

The hypothesis H1d was rejected. The results from the path model analysis showed that the path coefficient between IIS and KG was very weak and statistically insignificant. Therefore, it is inferred that there is no direct relationship between IIS and KG in the aggregate-level path model analysis.

The proposed hypothesis for the direct impact of IIS on KI was revealed to be statistically significant. Therefore, H1e was supported, implying that manufacturing companies' KI performance would suffer from the direct impact of IIS. In addition, IIS is the only factor that has a negative impact on KI in the Lean-KMPs model, its sub-factor INCOMPA has the strongest total effect to KI among other sub-components: INFLEX, LEEF, and CM. Thus, manufacturing companies should make sure their different IT systems are compatible with each other so that data, information and knowledge can be stored and transferred efficiently and effectively.

The hypothesis H1f was rejected in this research since the path coefficient between IIS and KE was very weak and statistically insignificant. Therefore, it is inferred that there is no direct relationship between IIS and KE.

Well-developed IT systems have played an important role in processing, storing, and real-time transferring transactional data and information among business members in the past twenty years (Ruivo et al., 2012). It connects every business function and unit in a supply chain through seamless information flow for supporting decision makers to develop comprehensive forecasts, plans, and marketing strategies (Saade and Nijher, 2016). However, unlike other driver factors (i.e., LQI, IKI, and IUVI) in the Lean-KMPs model, IIS did not show a significant direct impact on KE as expected. This may be because there are some moderating effects between IIS and KE. Moderation is the third variable that affects the strength or even the direction of a relationship between two constructs (Hair et al., 2017). In addition, it would not be reasonable to state that a well-developed IT system does not have a positive impact on manufacturing companies' KE performance. Product sales is one of the most important criteria for evaluating KE performance. An integrated ERP system can track purchase order history and identify customer ordering patterns, by which a sales manager can make better forecast. In addition, due to its scheduling feature, the manager can also see the upcoming production capacity from the ERP system (Jabbar et al., 2019). By combining the forecast data and capacity data, an effective marketing strategy can be made, so that the sales performance could be boosted. Therefore, it is reasonable to believed that a well-developed IT system may have an indirect positive impact on companies' KE performance.

H1g and H1h: Low quality information (LQI) has negative impacts on KG and KE

The hypothesis H1g was supported, as the aggregate-level path model analysis indicated that LQI has a substantial negative impact on KG at a significance. The result implied that low quality information can significantly undermine manufacturing companies' ability in decision making, planning, forecasting, product and service design, and problem solving. In addition, in the Lean-KMPs model, LQI and *Insufficient Knowledge Inventory* (IKI) are the two latent constructs have negative impacts on KG. By comparing the relative importance of these two constructs, the result revealed that LQI has higher relative importance on KG than that of IKI. Moreover, by ranking the total effects of the sub-factors of LQI and IKI, it is found that the two sub-factors of LQI: *Low Quality Downstream Information* (LQDI) and *Low Quality Upstream Information* (LQUI), have the strongest total effects on KG. The total effect of IKI's sub-factors: *Lack of Interactional Knowledge Inventory* (LIKI), Lack of Environmental Knowledge Inventory (LEKI), and Lack of Functional Knowledge Inventory (LFKI), are relatively smaller, which suggest that if a company does not have enough resources, they should focus more on improving the information quality (i.e., accuracy, accessibility, reliability, and timeliness) over increasing knowledge inventory in order to have better KG performance.

The proposed association from LQI to KE was found to be significant. Therefore, the hypothesis H1h was supported, implying that companies' products and services can be negatively influenced by using low quality information and knowledge in customer services, demand forecasting, and product design. In addition, LQI and IKI are the two latent constructs that have negative impacts on KE. By comparing the relative importance of these two constructs, the result revealed that LQI has higher relative importance on KE than that of IKI. In total effects comparison, LQDI and LQUI are the two strongest sub-factors on KE. The total effects of the rest sub-factors: LEKI, LIKI, and LFKI, are relatively smaller. These results suggest that if a company does not have enough resources, they should focus more on improving the information quality over increasing knowledge inventory in order to have better KE performance.

H1i, H1j, and H1k: Insufficient knowledge inventory (IKI) has negative impacts on KA, KG, and KE

The hypothesis H1i was rejected in this research since the path coefficient between IKI and KA was very weak and statistically insignificant. Therefore, it indicates that there is no direct relationship between IKI and KA. The reason to explain this result could be that most information shared within a manufacturing supply chain are transactional and operational information. When a company join a supply chain, all necessary information that needs to be shared is clearly defined and contracted in order to maximise the mutual benefit between members (Guo et al., 2015). Therefore, even if the company is lack of interactional skills and experiences with its business partners, it still can get the needed data, information, and knowledge from them.

The hypothesis H1j was supported as the path coefficient between IKI and KG was statistically significant. This result implies that manufacturing companies' KG performance can be constrained by lack of necessary knowledge repositories. In addition, as mentioned before, since IKI and LQI are two negative factors to KG in the Lean-KMPs model, and their sub-components have substantial effects on KG, which implies that large companies should make an effort to improve on all five sub-components (i.e., LIKI, LFKI, LEKI, LQDI, and LQUI) of these two latent variables as they generally have more resources than small companies.

The path coefficient between IKI and KE was negative at a significance level of 1%. Therefore, the hypothesis H1k was supported. The result also suggested that resourceful companies should improve on all five sub-components of IKI and LQI in order to increase the popularity and sales of the products and services in the market.

The results of H1g, H1h, H1j, and H1k revealed that improving information quality plays relatively more important role than increasing information quantity does in companies' KG and KE. Indeed, with the rapid development of the Internet and advanced IT systems today, obtaining business information is no longer a laborious task for decision makers. Data and information quality is becoming increasingly significant, especially in connection with the increasing flood of data in daily business operations (Azeroual, 2020). High quality downstream information is one of the most important determinants for successful product development and effective marketing strategy making (Danese and Kalchschmidt, 2011). Accurate and timely information regarding suppliers' product quality, specific technique, public relations, production, and delivery capability is essential for stable productivity and effective collaboration strategy making. However, these results do not diminish the importance of sufficient knowledge repository on KE and KG. Knowledge repository is organisational memory and the capabilities for knowledge users to store and reuse information and knowledge in the future. Interactional knowledge inventory is the skills and knowledge base for solving conflicts or issues caused in the interactions with business partners. Functional knowledge inventory is accumulated when companies work closely with their suppliers in aspects such as production, logistics, inventory management, and product development (Johnson et al., 2004). Environmental knowledge inventory is knowledgebase about a company's external operating environment, such as competitors' information, market conditions, customers' preference and behaviours, and changes in laws and regulations. It is significant in an enterprise's strategic planning and product development (Johnson et al., 2004). However, too much information could cause information overload and increase the cost in collecting, maintaining, processing, and analysing. Thus, it is advisable for knowledge managers to find the sweet spot between information quality and quantity based on their resources and capabilities.

Impact of Lean-KM Principles on KMPs: Answering Research Question 5

H2a, H2b, H2c, H2d and H2e: Identification and usage of valuable information and knowledge (IUVI) has positive impacts on KA, KS, KG, KI and KE

The hypothesis H2a was supported as the path coefficient between IUVI and KA was statistically significant. This result implies that manufacturing companies' ability of acquiring necessary information and knowledge from external environment can be enhanced by improving their information flow from four aspects: *Relevancy* (RELEV); *Timeliness and Accuracy* (T&A); *Scarcity* (SCAR); and *Accessibility* (ACCES). In addition, IUVI and *Encouraging Information and Knowledge Flow* (EIKF) are the two latent constructs that positively affect KA in the Lean-KMPs model. By ranking the relative importance of these two constructs, the result revealed that EIKF has higher relative importance on KA than that of IUVI. In total effects comparison, the sub-factor of EIKF--*Trustful Relationship with Business Partners* (TRP) is the strongest factor to KA. ACCES is the second strongest factor. The total effects of other sub-factors in IUVI (i.e., T&A, RELEV, and SCAR) were ranked at number 5, 6, and 7, respectively. These results suggest that resourceful companies should make an effort to cover both EIKF and IUVI in order to have better KA performance since the relative importance of these two latent variables are very similar.

The proposed association from IUVI to KS was found to be significant, since the path coefficient between them was statistically significant. Therefore, the hypothesis H2b was supported, implying that IUVI can improve manufacturing companies' ability in identify and select the required information and knowledge for completing their tasks. In addition, since IUVI is the only factor that brings positive impact on KS in the Lean-KMPs model, and its sub-components: RELEV has the largest total effect compare to that of other sub-components: T&A, ACCES, and SCAR, it is advisable for less resourceful companies to focus on information relevancy so as to improve their KS performance. For large and resourceful companies, they should cover all four sub-components at the same time.

The hypothesis H2c was rejected in the aggregate-level path model analysis since the path coefficient between IUVI and KG was very weak and statistically insignificant. Therefore, it indicates that there is no direct relationship between IUVI and KG.

The hypothesis H2d was supported as the path coefficient between IUVI and KI was statistically significant. This result implies that knowledge sharing and storage within an organisation can be significantly enhanced by the Lean-KM Principle IUVI. In addition, IUVI and EIKF are the two driver constructs that positively affect KI in the Lean-KMPs model. The relative importance of IUVI is higher than that of EIKF. In total effects comparison, the ACCES has strongest total effect on KI. The total effects of other sub-factors in IUVI (i.e., RELEV, T&A, and SCAR) were ranked at number 3, 6, and 7, respectively. These results suggest that resourceful companies should make an effort to cover both IUVI and EIKF in order to have better KI performance since the relative importance of these two latent variables are very similar.

The hypothesis H2e was supported as the path coefficient between IUVI and KE was statistically significant at a 5% level. This result implies that manufacturing companies' products and services can be significantly enhanced by using valuable information and knowledge in product and service design. In addition, since IUVI is the only factor that brings positive impact on KE in the

Lean-KMPs model, and its sub-components: T&A has the biggest total effect compare to that of other sub-components: SCAR, RELEV, and ACCES, it is advisable for less resourceful companies to focus on information timeliness and accuracy so as to improve their KE performance. For large and resourceful companies, they should cover all four sub-components at the same time.

H2f, H2g and H2h: Encouraging information and knowledge flow (EIKF) has positive impacts on KA, KG, and KI.

The proposed association from EIKF to KA was found to be significant since the path coefficient between them was statistically significant at a 1% level. Therefore, the hypothesis H2f was supported, implying that EIKF can improve manufacturing companies' ability in acquiring critical information and knowledge from external environment for completing their tasks. In addition, as mentioned before, EIKF and IUVI are the two latent constructs that positively affect KA. EIKF has higher relative importance on KA than that of IUVI. In total effects comparison, the sub-factor TRP has strongest total effect on KA. The total effects of other sub-factors in EIKF (i.e., *Expanding Communication Channel* (ECC), *Trustful Environment with Organisation* (TEO), and *Shared Language* (SL)) were ranked at number 3, 4, and 8, respectively. These results suggest that resourceful companies should make an effort to cover both EIKF and IUVI in order to have better KA performance since the relative importance of these two latent variables are very similar. As for less resourceful and small companies, they should focus on building trustful relationships with business partners and enhancing the accessibility of necessary knowledge and information flowing within their supply chain.

The hypothesis H2g was rejected in the aggregate-level path model analysis as the path coefficient between EIKF and KG was very weak and statistically insignificant. Therefore, it indicates that there is no direct relationship between EIKF and KG.

The hypothesis H2h was supported as the path coefficient between EIKF and KI was statistically significant at a 1% level. This result implies that knowledge sharing and storage within an organisation can be significantly enhanced by the Lean-KM Principle EIKF. Moreover, as previously mentioned, EIKF and IUVI are the two positive latent variables to KI in the Lean-KMPs model. IUVI has a slightly higher relative importance than EIKF. In total effects comparison, EIKF's sub-factor TEO has the second strongest total effect on KI. The total effects of other sub-factors in EIKF (i.e., ECC, SL, and TRP) were ranked at number 4, 5, and 8, respectively. These results imply that resourceful companies should make an effort to cover both IUVI and EIKF in order to have better KI performance since the relative importance of these two latent variables are very similar, less resourceful and small companies should focus on enhancing the accessibility of necessary knowledge and information flowing within their company and encouraging trustful and friendly relationships between colleagues.

Findings in Multi-group Analyses: Answering Research Question 6

In the multi-group analyses, all the path model relationships do not differ significantly between China and the USA. The results of hypotheses testing are also the same as that of the aggregate-level path model analysis. It is reasonable to believe that the essence of manufacturing industry is the same no matter in which country.

In business sizes comparison, most hypotheses testing results do not differ significantly between SMEs and large businesses. The only exceptions are the hypotheses H1d: IIS→KG, H2c: IUVI→KG, and H2f: EIKF→KA. Regarding H1d, the effect between IIS and KG is significantly different between SMEs and large companies. This result reveals that large companies' KG performance can be significantly undermined by badly developed IT systems. As for H2c, the relationship between IUVI and KG is significantly different between SMEs and large enterprises. It implies that large enterprises' ability in decision making, planning, forecasting, and problem solving can be significantly improved by the

Lean-KM Principle IUVI. With respect to H2f, the effect EIKF on KA is significantly different among SMEs and large enterprises. This result implies that EKIF is more important to large companies than to SMEs in improving KA performance.

In industrial comparison, H2c and H2g are significantly different between food and drink industry and machinery and electronics manufacturing. The result suggested that IUVI and EIKF can significantly enhance machinery and electronics manufacturing's KG performance.

These results can be explained from five aspects. Firstly, unlike food and drink industry, large machinery and electronics manufacturing's market demands are unstable, and the cost of production is high. Therefore, they usually are sensitive to the changes (e.g. demand and supply fluctuations, technology changes, regulation changes, and threat from competitors) from the external environment. Most of them tend to adopt assemble-to-order or engineer-to-order production strategies in order to eliminate inventory and middleman, so that they can reduce cost and react quickly to the changes. They need to constantly open to new ideas and acquire new information or knowledge from the outside world to deal with these changes. Food and drink SMEs, on the other hand, their market demands are relatively stable, and the cost of production is low. They usually adopt make-to-stock or make-to-plan production strategy. Therefore, food and drink SMEs do not need to collect information and knowledge as frequently and quickly as their counterpart. Secondly, comparing with large machinery and electronics manufacturing, especially high-tech companies, the new product introduction rate is very low in food and drink SMEs. Over 100 years old recipes are still in use in many tradition brands, such as wine-making industry. Their brand and reputation will be damaged if they want to follow the trend and change their traditional recipe. Consequently, they do not have much pressure to acquire new knowledge and technology for innovation. Thirdly, many food and drink companies are local companies. They have brand and regional advantages. Such as Tsingtao Brewery, it has 117 years history and is the most famous beer brand in Shandong province of China. When people want to drink beer in the summer, the first brand appears in their mind is Tsingtao beer. Such kind of companies have no competitors in their region. Accordingly, it is not necessary for them collecting business information to develop better marketing strategies or upgrade their products as frequently as their counterparts: machinery and electronics manufacturing. Fourthly, generally large companies are the focal companies of their complex supply network. In contrast with small companies, they need to handle much larger volume of transactional and operational data and information from upstream and downstream of their supply network. Without the help of well-functioning IT systems, it is impossible for manpower to process such large amount of information and make sound decisions. Lastly, as focal companies, it is necessary to have skills, commitment and resources for developing trustful relationships with business partners and creating smooth communication channels in order to lead and coordinate every member to operate their supply chain effectively and efficiently. As for small or subordinate companies, however, such skills and resources are not must-haves. The abovementioned five points explained why IIS, IUVI, and EIKF have stronger impacts on large and machinery and electronics manufacturing than on SMEs and food and drink industry.

7.3 Summary

This chapter discussed how the six research questions have been answered. It also discussed and explained how different between the conceptual theories and empirical findings in this research. The next chapter concludes this study by highlighting the implications drawn from these results. It will also acknowledge the study’s limitation and identify potential areas of further research.

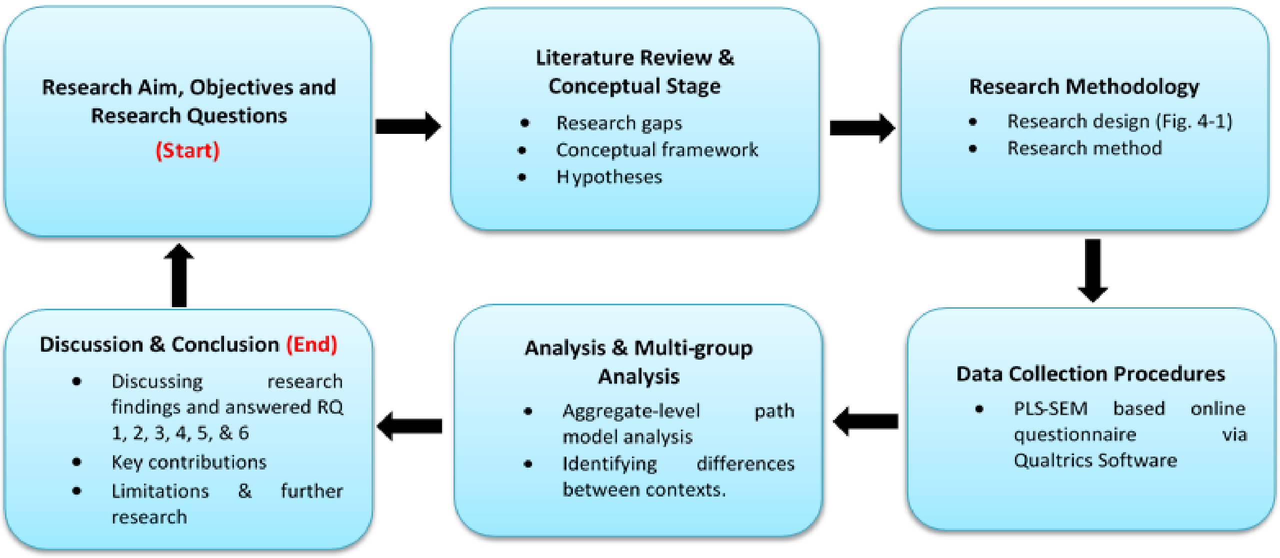
Chapter 8 Conclusion

This chapter concludes the thesis. It starts with an overall view of the research. Next, the major finding obtained in this research are briefly recalled. These findings are linked to the research objectives set in Chapter 1. Afterward, the contributions and research implications are discussed and divided into theoretical and managerial implications. Finally, the research limitation and future research directions are linked together and discussed in the last section of this chapter.

8.1 An Overall View of the Research Project

Before concluding this research, it is necessary to look at the big picture of the whole project and discuss how the study has answered research questions and bridged the research gaps by contributing to the existing knowledge. **Figure 8-1** illustrates the links across all stages of the project by visualising key research activities.

Figure 8-1 Links across All Stages of the Project



The aim of this research is to eliminate inefficient knowledge management activities and use Lean Principles as guidance to improve knowledge management performance in manufacturing supply chains. In order to achieve this aim, five research objectives and six research questions were developed in Chapter 1. To answer these questions and fulfil the research objectives, this study conducted a rigorous literature review on supply chain KM, Lean thinking and Lean KM in Chapter 2. It helps the researcher to understand the related theories and find research gaps. In Chapter 3, a conceptual model (i.e., Lean-KMPs) and two main research hypotheses which contains 19 sub-hypotheses were developed for the empirical test. By the end of Chapter 3, the first three research questions were answered. In Chapter 4 and 5, the research methodology and data collection procedures were discussed in order to justify the methods that have been selected for testing the proposed model and hypotheses in Chapter 3. Subsequently, to answer the research question 4, 5 and 6, this study empirically examined the proposed hypotheses in Chapter 6. It firstly provided a descriptive analysis based on the survey responses. Next, the proposed research model and hypotheses were tested in an aggregated-level path model analysis by partial least squares structural equation modelling (PLS-SEM). A series of analysis procedures were conducted to examine each measurement's reliability and validity, model's predictive capabilities, causal relationship between *Knowledge Management Processes* (KMPs), *Lean-KM Wastes* and *Lean-KM Principles*. In the last section of Chapter 6, three multi-group analyses were conducted so as to identify the differences when the Lean-KMPs model is applied in different contexts including two types of manufacturing industries (i.e. machinery and electronics manufacturing and food and drink industry), two types of business sizes (i.e. SMEs and Large companies), and two countries (i.e. China and the US). In Chapter 7 and 8, the research findings, key contributions and further research directions were summarised and discussed. By the end of Chapter 8, all the six research questions and five research objectives were answered and achieved.

8.2 Main Conclusions

Knowledge is power. Today, more and more companies have realised that knowledge is their valuable organisational resource from a strategic perspective and a foundation for competitive advantage. Companies must efficiently and effectively create, capture, and share knowledge in order to solve problems and exploit opportunities. Therefore, how to improve knowledge management performance has become a popular topic in the recent decades. KM is a systematic approach to manage the use of information in order to provide a continuous knowledge flow to the right people in the right format at the right time in order to support successful decision making. In the context of supply chain management, KM can improve communications within business partners, and provide more informed knowledge by sharing best practices, lessons learned, and the rationale for strategic plans and decisions. Unfortunately, many organisations find that successful KM is an uphill struggle and its benefits elusive. Lean thinking has been studied and applied in global manufacturing industries for more than twenty years in order for companies to eliminate wastes in all aspect of their business. Since the similarity between KM and manufacturing system, Lean thinking has been proved by several researchers that it can be integrated with KM system. However, most of these studies were conducted in service and high-tech industries, only very few studies are related to manufacturing industry. Therefore, for the abovementioned reasons, this research attempted to integrate Lean thinking into KM of manufacturing supply chains for improve their KM performance by adopting a comprehensive approach simultaneously exploring the effects of both Lean-KM Wastes and Lean-KM Principles on knowledge management processes of manufacturing companies.

There are five main conclusions to respond the five research objectives of this research. Firstly, through a comprehensive review of fifteen related studies, the researcher identified five common underlying KMPs (see Table 2-1), which include 1) acquisition--/--collection--/--capture; 2) selection--/--identification--/--

organising; 3) creation--/--generation--/--innovation--/--adaptation; 4) retention--/--storage--/--retrieval--/--dissemination; 5) application--/--utilisation. Hence, Holsapple and Singh (2001)'s knowledge chain model was adapted in this research for representing the full KMPs, because its five KMPs are very similar the five common features above. These five KMPs include knowledge acquisition, selection, generation, internalisation, and externalisation.

Secondly, inefficient KM activities or as being called "*Wastes*" in the Lean thinking are regarded as the barriers to prevent information/knowledge flow and reduces information users' ability to access their required information and knowledge. Efficient KM activities are considered as value-adding activities in the KMPs, which can be achieved by the guidance of The Lean-KM Principles. Inspired by the works of Womack and Jones (1996) and Hicks (2007), four Lean-KM Wastes and two Lean-KM Principles were developed in this research for enhancing the KM performance of manufacturing supply chains. The four Lean-KM Wastes include: *Information Overload*, *Inappropriate Information System*, *Low Quality Information*, and *Insufficient Knowledge Inventory*. The two Lean-KM Principles include: *Identification and Usage of Valuable Information and Knowledge* and *Encouraging Information and Knowledge Flow*.

Thirdly, based on the four Lean-KM Wastes, 11 hypotheses were developed in order to examine how and to what extent these Wastes negatively affect the five KMPs. Through the aggregate-level path model analysis, the results confirmed that *Information Overload* (IO) has a significant negative impact in *Knowledge Selection* (KS), *Inappropriate Information System* (IIS) has significant negative impacts on *Knowledge Acquisition* (KA), *Knowledge Internalisation* (KI) and *Knowledge Externalisation* (KE), *Low Quality Information* (LQI) has significant negative impacts on *Knowledge Generation* (KG) and KE, as well as *Insufficient Knowledge Inventory* (IKI) has significant negative impacts on KG and KE. In addition, the results also revealed that IO does not have a negative impact on KG as expected, rather the opposite, it has a significant positive impact on KG, IIS did not show any direct impact on KG and KE, same as IKI to KA.

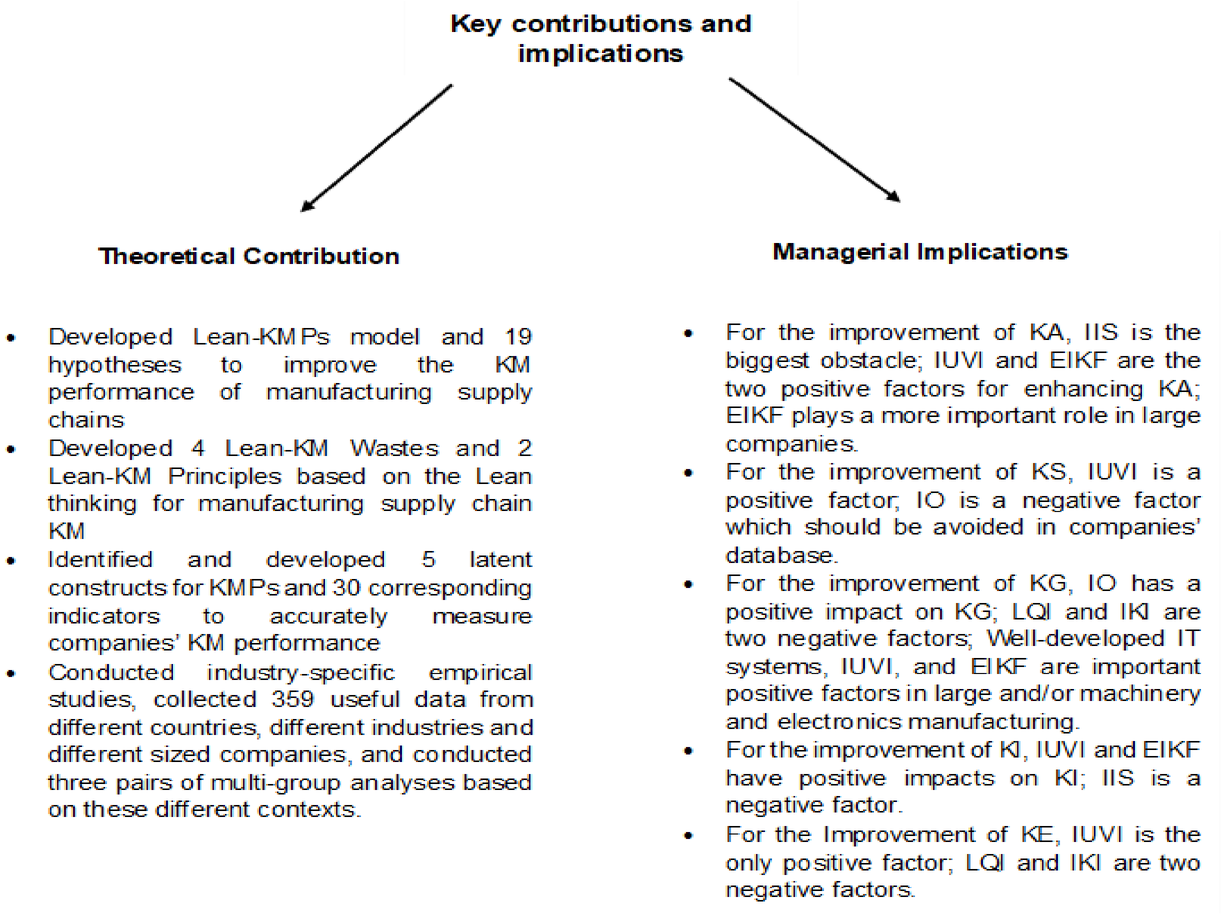
Fourthly, based on the two Lean-KM Principles, 8 hypotheses were developed. The results confirmed that *Identification and Usage of Valuable Information and Knowledge* (IUVI) has significant positive effects on KA, KS, KI and KE. However, *Encouraging Information and Knowledge Flow* (EIKF) has a significant positive impact only on KI in the aggregate-level path model analysis. The results rejected that IUVI has a positive effect on KG, and EIKF has positive effects on both KA and KG.

Fifthly, the multi-group analysis has been conducted in three different contexts, namely, Country China vs. the US, Industry machinery and electronics manufacturing vs. food and drink, business size SMEs vs. large enterprises. In country comparison, the results of hypotheses testing were similar to those of the aggregate-level path model analysis, and there was no statistic difference between these two countries. In business sizes comparison, most results did not differ significantly between SMEs and large businesses. However, the hypotheses H1d and H2c were supported only in the context of large companies, which means IIS and IUVI have significant negative and positive impacts on KG of large companies, respectively. In addition, the results also revealed that H2f was supported in both circumstances, but EKIF has stronger impact on KA in large companies than in SMEs. Lastly, regarding industrial comparison, H2c and H2g were only supported in the context of machinery and electronics manufacturing, which implies that IUVI and EIKF are more important to machinery and electronics manufacturing than to food and drink companies in improving KG performance.

8.3 Contributions and Research Implications

The key contributions and implications of this study are described separately from theoretical and managerial perspectives as summarised in **Figure 8-2.**

Figure 8-2: Summary of Key Research Contributions and Implications



8.3.1 Theoretical Contributions

This study has investigated the integration of Lean thinking with knowledge management processes (i.e. knowledge acquisition, knowledge selection, knowledge generation, knowledge internalisation, and knowledge externalisation) to improve the KM performance of manufacturing supply chains and help them to be successful. The study contributes to the supply chain knowledge management literature in several ways. First, most Lean-KM related studies were conducted in service and high-tech companies, such as health care, engineering and IT development, since these companies are knowledge-intensive industries comparing to the manufacturing sector and their KM issues usually are spotted relatively early and easily (Redeker et al., 2019). This research brought the Lean thinking back to its origin place—the manufacturing industries to improve their KM performance. In this respect, an innovative conceptual framework (i.e. Lean-KMPs) and 2 main hypotheses that were comprised of 19 sub-hypotheses were developed in order to test how well the Lean thinking can be fitted with the manufacturing industries' KMPs.

Second, due to lack of common definition of Lean-KM for the manufacturing supply chain context in the extant literature, there are no tailored Lean-KM practices for this context. In order to fill this gap, the author of this research has developed 4 Lean-KM Wastes and 2 Lean-KM Principles through rigorous review and analysis of the literature. As second order constructs, these 6 Lean-KM practices also include 20 first order constructs (i.e. sub-factors) and 75 indicators, so as to accurately measure the more abstract second order constructs and enrich the theoretical concepts (see Table 6-10, 5-2 and 5-3). These first and second order constructs developed and validated were parsimonious and pertinent, and measurement models' testing revealed that the measurement scales were reliable and valid. They met the requirements for internal consistency, convergent validity, discriminant validity, collinearity test, and significance and relevance test. Therefore, these constructs can be adopted in other relevant research in the future.

Third, the literature review highlighted the relative lack of a holistic approach for improving the whole knowledge management processes. Instead, previous research efforts mainly focused on using Lean thinking to improve companies' knowledge sharing or knowledge generation related activities. A holistic approach was adopted in this research where the 5 knowledge management processes (i.e. KA, KS, KG, KI, and KE) were identified, and 5 corresponding constructs as well as 30 indicators were developed in order to provide a comprehensive picture on the determinants of knowledge management performance (see Table 5-4). Hence, this approach has the potential to deliver considerably greater benefit for manufacturing supply chains. In addition, these KMPs constructs and their indicators also passed the validity and reliability test with empirical data and can be adopted for other research in the future.

Lastly, to answer the call from Gupta et al. (2016) for more rigorous industry-specific empirical studies and evidence on Lean-KM, the researcher collected 359 usable quantitative datasets which come from three different countries: China, the US and the UK; two types of manufacturing industries: machinery and electronics manufacturing, and food and drink industry; two different business sizes: SMEs and large enterprises. In addition, three pairs of multi-group analyses were conducted between countries, industries, and different sized companies to identify the differences when the Lean-KMPs model was applied in these different contexts. This research expanded the application of Lean-KM theory and would have greater implications for manufacturing practitioners to improve the KM performance with their supply chain partners.

8.3.2 Managerial implications

In addition to the theoretical contributions, this research has a number of contributions for manufacturing practitioners to improve their supply chain KM performance from five angles (i.e. KA, KS, KG, KI and KE). First, KA refers to a manufacturing company identifies and acquires needed information and knowledge from its external environment. Badly designed information systems, especially, lack of extended enterprise function, is the biggest obstacle for improving the performance of KA. Therefore, managers should make sure their IT systems can be integrated with those of their supply chain members so as to acquire necessary data and information effectively and efficiently. Moreover, IUVI and EIKF are two factors that can enhance KA. The results showed that companies, especially big companies, should build trustful relationships and improve the accessibility of required information with their supply chain members.

Second, KS means that a company selection of their required knowledge from their knowledge repository (i.e. database and knowledgebase) for decision making, planning and problem solving. In order to enhance the performance of KS, companies should only retain the most valuable information and knowledge just in case their databases are overloaded because keeping and maintaining ever-increasing out of date documents could significantly inhibit the performance of decision makers in retrieving critical information. However, it is important to have systems to archive historical information for the future usage. Company should remove out of date information from current operating knowledge systems and archive it securely and without risk of corruption. In addition, information provider should understand receiver's needs so as to provide the most relevant information, which could help receivers to store the information more effectively and also make the retrieval of it much easier, because once the information is acquire, receivers or users will store it in their databases based on its character and clear purpose.

Third, activities of KG include companies using their existing information and knowledge making decisions, solving problems, developing products and services, and creating managerial practices. The results suggested that companies should gather business information as comprehensive as they can in order to improve KG performance. In addition, LQI and IKI are two variables that have significant negative impacts on KG. By comparing their path coefficients and their sub-factor's total effects, the results suggested that less resourceful companies should focus more on improving the information quality (i.e. accuracy, accessibility, reliability, and timeliness) over increasing knowledge inventory in order to have better KG performance. Moreover, by multi-group analyses, the results indicated that well-developed IT systems, IUVI, and EIKF are important factors for large and/or machinery and electronics manufacturing's KG performance.

Fourth, KI is an activity that alters an organisation's knowledge resources by refining and updating its own knowledge repository. It includes knowledge sharing, knowledgebase modification, and knowledge storage. In the Lean-KMPs model, IIS is the biggest obstacle for KI. Thus, manufacturing companies should make sure their different IT systems are compatible with each other so that critical data, information and knowledge can be stored and transferred efficiently and effectively. Moreover, IUVI and EIKF are two positive factors to KI. Since their path coefficients and their sub-factors' total effects are relatively close, resourceful companies should make an effort to cover both IUVI and EIKF in order to have better KI performance.

Lastly, KE means that manufacturing companies use their existing knowledge and information to produce products and provide services to the target market. LQI and IKI are two negative factors to KE. LQI and its sub-factors have higher path coefficient and total effects than those of IKI. Hence, less resourceful companies should focus more on improving the information quality over increasing knowledge inventory in order to have better KE performance. Furthermore, IUVI is the only positive factor to KE. Its sub-factor *Timeliness and Accuracy* has the strongest total effect among other sub-factors (i.e. *Relevancy, Scarcity, and Accessibility*), but the differences between them are not huge. Hence, it is advisable for less resourceful companies to focus on information timeliness and accuracy to improve their KE, while for large and resourceful companies, they should cover all four sub-factors at the same time.

8.4 Limitations and Future Research

As in all studies, several limitations should be acknowledged. First, although the sample size (182 from China, 139 from the USA, and 38 from the UK) proved to be sufficient to conduct a robust statistical analysis, a larger sample would probably enhance the results. Collecting data from manufacturing companies' managers is often very challenging and generally the response rate barely exceeds 21%. In addition, gathering data from three different countries across two types of industries has made the process lengthier in time. For these reasons, the data collection process took more than seven months. Future studies could spend more time and resources, and therefore expand the sample size.

Second, based on a thorough literature review, the systematic approach adopted in this study attempted to include the most important positive and negative factors influencing manufacturing companies' KM performance. However, some factors, such as decision maker's experience in using IT systems which could be important predictors of knowledge externalisation performance, yet may have been neglected by the literature, and could have been missed in this study. For this reason, future research could comprise additional factors that could potentially mediate or moderate the effect of IIS on companies' KE or other KMPs' performance. In addition to the mediation or moderator variables, future research can also identify more positive and negative variables based on the concepts of four Lean-KM Wastes and two Lean-KM Principles (i.e. as sub-factors) to expand Lean-KM tools for further improvement of KM performance in manufacturing companies.

Third, the firms selected in this research were from two types of manufacturing sectors, the reason behind this choice was to answer the call for cross-sectorial studies raised in the literature. Cross-sectorial studies are believed to provide more generalisable findings. However, different types of companies encounter different types of problems and adopt different KM strategies. Therefore, future research could either involve more manufacturing sectors (e.g. chemical pharmaceutical companies and textile garment companies) and more industries (e.g. service and construction industries) or just focus on one sector.

Fourth, the present study employed a post-positivistic approach using quantitative questionnaires as a method of data collection between different contexts (China vs. the USA; SMEs vs. large Business; machinery and electronics manufacturing vs. food and drink industry). The results first allowed the study to explore the direct impacts of the four Lean-KM Wastes and two Lean-KM Principles on five knowledge management processes, and second revealed a number of differences by implementing the Lean-KMPs model in the abovementioned contexts. However, the post-positivistic approach could neither empirically provide an in-depth explanation on how these five KMPs are enhanced or constrained by the Lean-KM Wastes and Lean-KM Principles, nor uncover the factors leading to differences between different groups. Such in-depth explanations can only be achieved by an interpretive approach. Hence, future studies could adopt a qualitative methodology using in-depth interviews with business managers to increase understanding about how the identified KMPs can be improved by the Lean thinking, and the variations in different contexts.

Fifth, although the sample has been divided into three pairs of groups in multi-group analysis, more detailed partition can be made such as large machinery and electronics manufacturing, SME machinery and electronics manufacturing, large food and drink companies, and SME food and drink companies in order to find out more detailed differences when the Lean-KMPs model applied in these contexts.

Finally, this study was only conducted in developed countries' manufacturing industries. Hence, it is suggested to conduct more studies in developing countries in the future, such as in Vietnam, the Philippines, Thailand, Indonesia, India, Mexico, and Brazil. These countries are all new emerging economies which are believed to offer great potential for manufacturing and are in need to improve their supply chain KM performance. Therefore, such kind of studies would have important implications for both theory and practise.

8.5 Summary

This chapter summarised the research findings, contributions, research implications, limitations and future research directions. Although various industries such as government, healthcare, banking industry, education, engineering, and construction industry found considerable benefit from Lean-KM, Lean-KM in manufacturing supply chains in still in its infancy. Using multiple rigorous quantitative methods, the constructs and relationships in the Lean-KMPs model was examined to acquire a comprehensive understanding of how the 4 Lean-KM Wastes and 2 Lean-KM Principles influence the five knowledge management processes (KMPs). The findings by sing PLS-SEM models with the online-based survey in different contexts confirmed that Lean-KM Wastes and Lean-KM Principles have negative and positive impacts on KMPs, respectively. Various manufacturing companies in both heavy and light industries, especially, machinery and electronics manufacturing and food and drink industry, would benefit from applying the results of this study to improve their KM performance. The results suggest that manufacturing practitioners should use a comprehensive approach to improve knowledge management processes in order to make sure that critical information and knowledge flow seamlessly and efficiently among their supply chain members, further to achieve successful supply chain integration.

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Appendix A: A Summary of the Highly Relevant Articles

No.	Author(s)	Year	Title	Publication	Country	Method
1	Chang, L., Zou, S., & Li, S.	2001	*Research of influential elements on knowledge diffusion based on knowledge chain*	Science Development and Countermeasures	China	Interviews
2	Holsapple, C.W., & Singh, M.	2001	*The knowledge chain model—activities for competitiveness*	Expert Systems with Applications	USA	Survey
3	Farhoomand, A.F., & Drury, D.H.	2002	*Managerial information overload*	Communications of the ACM	Australia, China, UK, USA	Survey
4	Hick, B.J., Culley, S.J., Allen, R.D., & Mullineus, G.	2002	*A framework for the requirements of capturing, storing and reusing information and knowledge in engineering design*	International Journal of Information Management	UK	Theory
5	Holsapple, C.W., & Joshi, K.D.	2002	Knowledge management: a threefold framework	The Information Society	USA	Theory
6	Cormican, K., & O'Sullivan, D.A.	2003	*Collaborative knowledge management tool for product innovation management*	International Journal of Technology Management	Ireland	Interviews
7	Eppler, M., & Mengis, J.	2004	*The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines.*	The Information Society	Switzerland	Theory
8	Johnson, J.L., Sohi, R.S., & Grewal, R.	2004	*The role of relational knowledge stores in*	Journal of Marketing	USA	interviews and case study

			interfirm partnering			
9	Kwon, I.W.G., & Suh, T.	2004	*Factors affecting the level of trust and commitment in supply chain relationships*	The Journal of Supply Chain Management: A Global Review of Purchasing and Supply	USA	Interviews and survey
12	Xue, Y., Liang, H., Boulton, W.R., & Snyder, C.A.	2005	*ERP implementation failures in China: case studies with implications for ERP vendors*	International Journal of Production Economics	China	Interviews
11	Gu, X., Li, J., & Wang, W.	2005	*Knowledge chain, knowledge chain management and knowledge advantage*	International Conference on Services Systems and Services Management	China	Theory
10	Cabrera, E., & Cabrera, A.	2005	*Fostering knowledge sharing through people management practices*	International Journal of Human Resource Management	USA	Theory
13	Chiu, C., Hsu, M., & Wang, E.T.G.	2006	*Understanding knowledge sharing in virtual communities: an integration of social capital and social cognitive theories*	Decision Support Systems	China	Survey
14	Hicks, B.J., Culley, S.J., & McMahon, C.A.	2006	*A study of issues relating to information management across engineering SMEs*	International Journal of Information Management	UK	Interviews
18	Law, C.C.H., & Ngai, E.W.T.	2007	*ERP systems adoption: an exploratory study of the organisational factors and impacts of ERP success*	Information & Management	China	Survey
15	Forslund, H., & Jonsson, P.	2007	*The impact of forecast information quality on supply*	International Journal of Operations & Production Management	Sweden	Survey

			chain performance			
16	Hicks, B.J.	2007	*Lean information management: understanding and eliminating waste*	International Journal of Information Management	UK	Interviews
17	Klausegger, C., Sinkovics, R.R., & Zou, H.	2007	*Information overload: a cross-national investigation of influence factors and effects*	Marketing Intelligence & Planning	USA, UK	Survey
19	Cheung, M., & Myers, M.B.	2008	*Managing knowledge sharing networks in global supply chains*	International Journal of Management and Decision Making	Australia	Survey
23	Renzl, B.	2008	*Trust in management and knowledge sharing: the mediating effects of fear and knowledge documentation*	Omega: The International Journal of Management Science	Austria	Interviews and survey
20	Daud, S., & Yusuf, W.F.W.	2008	*An empirical study of knowledge management processes in small and medium enterprises*	Communications of the IBIMA	Brazil	Theory
24	Mu, J., Peng, G., & Love, E.	2008	*Interfirm networks, social capital, and knowledge flow*	Journal of Knowledge Management	China	Interviews
21	Lumsden, K., & Mirzabeiki, V.	2008	*Determining the value of information for different partners in the supply chain*	International Journal of Physical Distribution & Logistics Management	Sweden	Interviews
25	Lumsden, K., and Mirzabeiki, V.	2008	*Determining the value of information for different partners in the supply chain*	International Journal of Physical Distribution & Logistics Management	Sweden	Theory
22	Parry, G., & Graves, A.	2008	*The importance of knowledge management for ERP systems*	International Journal of Logistics	UK	Interviews and case study

				Research and Applications		
30	Tseng, S.	2009	*A study on customer, supplier, and competitor knowledge using the knowledge chain model*	International Journal of Information Management	China	Interviews and case study
29	Michnik, J., & Lo, M.C.	2009	*The assessment of the information quality with the aid of multiple criteria analysis*	European Journal of Operational Research	China	Interviews and survey
27	Chen, Y., Shang, R., & Kao, C.	2009	*The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment*	Electronic Commerce Research and Applications	China	Survey
28	Kuo, R.Z., & Lee, G.G.,	2009	*KMS adoption: the effects of information quality*	Management Decision	China	Survey
26	Bicheno, J., & Holweg, M.	2009	*The lean toolbox: the essential guide to lean transformation*	PICSIE Books	UK	Theory
32	Hölttä, V., Mahlamäki, K., Eisto, T., & Ström, M.	2010	*Lean information management model for engineering changes*	World Academy of Science, Engineering and Technology	Finland & Sweden	Interviews and case study
31	Claro, D.P., & Claro, P.B.O.	2010	*Collaborative buyer-supplier relationships and downstream information in marketing channels*	Industrial Marketing Management	Netherlands	Survey
33	Karr-Wisniewski, P., & Lu, Y.	2010	*When more is too much: operationalising technology overload and exploring its impact on knowledge*	Computers in Human Behaviour	USA	Survey

			worker productivity			
36	Staats, B.R., Brunner, D.J., & Upton, D.M.	2011	*Lean principles, learning, and knowledge work: evidence from a software services provider*	Journal of Operation Management	India	Interviews and case study
35	Dahlgaard, J.J., Pettersen, J. & Dahlgaard-Park, S.M.	2011	*Quality and lean health care: a system for assessing and improving the health of healthcare organisations*	Total Quality Management and Business Excellence	Sweden	Survey
34	Bell, S.C., & Orzen, M.A.	2011	*Lean IT: enabling and sustaining your lean transformation*	New York: Productivity Press	USA	Theory
37	Du, T.C., Lai, V.S., Cheung, W., & Cui, X.	2012	*Willingness to share information in a supply chain: a partnership-data-process perspective*	Information & Management	China	Survey
38	Schiuma, G., Carlucci, D., & Lerro, A.	2012	*Managing knowledge processes for value creation*	The Journal of Information and Knowledge Management Systems	Italy	Theory
39	Choi, T.M., Chow, P.S., & Liu, S.C.	2013	*Implementation of fashion ERP systems in China: case study of a fashion brand, review and future challenges*	International Journal of Production Economics	China	Interviews and case study
40	Josson, P., and Mattsson, S.A.	2013	*The value of sharing planning information in supply chains*	International Journal of Physical Distribution & Logistics Management	Sweden	Mathematical modelling
41	Gong, Q., Yang, Y., & Wang, S.	2014	*Information and decision making delays in MRP, KANBAN, and CONWIP*	International Journal of Production Economics	China	Mathematical model
43	Zhou, H., Shou, Y., Zhai, X., Li,	2014	*Supply chain practice and*	International Journal of	China	Survey

	L., Wood, C., and Wu, X.		*information quality: a supply chain strategy study*	Production Economics	USA	
42	Soares, S., & Teixeira, L.	2014	*Lean information management in industrial context: an experience based on a practical case*	International Journal of Industrial Engineering and Management Science	Portugal	Interviews and case study
45	Liu, S., Moizer, J., Megicks, P., Kasturiratne, D., & Jayawickrama, U.	2014	*A knowledge chain management framework to support integrated decisions in global supply chains*	Production Planning & Control	UK	Interviews
44	Pan, J., Liu, S., Tuck, S., & Alkuraiji, A.	2014	*A framework for optimising inventory level of global critical knowledge to support group decision making*	Group Decision and Negotiation	UK	Theory
46	Liu, S., Smith, M.H., Tuck, S., Pan, J., Alkiraiji, A., & Jayawickrama, U.	2014	*Where can knowledge-based decision support systems go in contemporary business management—a new architecture for the future*	Journal of Economics, Business and Management	UK	Theory
48	Dehnavi, M.A.	2015	*Improving knowledge management by means of lean thinking: a case study of project lessons learned exchange at the engineering department of Janssen Biologics (PhD thesis)*	Delft University of Technology	Belgium	Interviews and case study
49	Gong, Y., & Janssen, M.	2015	*Demystifying the benefits and risks of lean service innovation: a*	Journal of Systems and Information Technology	China	Interviews and case study

			banking case study			
51	Malaurent, J., & Avison, D.	2015	*From an apparent failure to a success story: ERP in China-Post implementation*	International Journal of Information Management	China	Interviews and case study
50	Iuga, M.V., Kifor, C.V., & Rosca, L.I.	2015	*Lean information management: criteria for selecting key performance indicators at shop floor*	Academic Journal of Manufacturing Engineering	Romania	Theory
47	Cannella, S., Framinan, J.M., Bruccoleri, M., Barbosa-Povoa, A.P., & Relvas, S.	2015	*The effect of inventory record inaccuracy in information exchange supply chains*	European Journal of Operational Research	Spain, Chile, Italy, Portugal	Mathematical model
52	McDermott, C.M., & Venditti, F.J.	2015	*Implementing lean in knowledge work: implications from a study of the hospital discharge planning process*	Operations Management Research	USA	Interviews and case study
54	Zhao, P., Rasovska, I., & Rose, B.,	2016	Integrating lean perspectives and knowledge management in services: application to the service department of a CNC manufacturer	IFAC-PapersOnLine	China	Interviews and case study
53	Zhang, L., & Chen, X.	2016	*Role of lean tools in supporting knowledge creation and performance in lean construction*	Procedia Engineering	China	Survey
55	Gong, Y., & Blijleven, V.	2017	*The role of Lean principles in supporting knowledge management in IT outsourcing relationships*	Knowledge Management Research & Practice	Netherlands	Interviews and case study
56	Olaisen, J., & Revang, O.	2017	*The dynamics of intellectual property rights*	International Journal of	Norway	Interviews

			for trust, knowledge sharing and innovation in project teams	Information Management		
57	Santhiapillai, F.P., & Chandima Ratnayake, R.M.	2018	*Identifying and defining knowledge-work waste in product development: a case study on lean maturity assessment*	Proceedings of the 2018 IEEE	Norway	Interviews and case study
58	Panahifar, F., Byrne, P.J., Salam, M.A., & Heavey, C.	2018	*Supply chain collaboration and firm's performance: the critical role of information sharing and trust*	Journal of Enterprise Information Management	Thailand	Survey
61	Redeker, G.A., Kessler, G.Z., & Kipper, L.M.	2019	*Lean information for lean communication: analysis of concepts, tools, references, and terms*	International Journal of Information Management	Brazil	Theory
62	Kamble, S., Gunasekaran, A., & Dhone, N.C.	2019	*Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies*	International Journal of Production Research	India	Survey
60	D'Andreamatteo, Ianni, L., Rangone, A., & Paolone, F.	2019	*Institutional pressures, isomorphic changes and key agents in the transfer of knowledge of lean in healthcare*	Business Process Management Journal	Italy	Interviews and case study
59	Balocco, R., Cavallo, A., Ghezzi, A., & Barbegal-Mirabent, J.	2019	*Lean business models change process in digital entrepreneurship*	Business Process Management Journal	Italy	Survey and interviews
63	Kerdpitak, C. & Jermsittiparsert, K.,	2020	*Bridging engineering education with lean manufacturing*	Test Engineering and Management	Malaysia	Survey

			through teamwork, awareness of lean information and employee involvement			

Appendix B: Questionnaire (English Version)

Knowledge Management Performance in Manufacturing Industries

Dear Sir/Madam,

This survey is part of a PhD project on “How to use Lean thinking to improve knowledge management performance in the context of manufacturing supply chain” with Plymouth University. To ensure your anonymity, all of your answers are sent directly to the secure university database. Your completed survey answers will be only seen by research team. If you wish to stop completing the survey at any time, please feel free to do so.

This survey is comprised of 4 parts. Part 1 is the profile information about you and your company. Part 2 is about the non-value adding activities in knowledge management that may exist in your organisation. Part 3 is about the value adding activities in knowledge management that may be conducted in your company. Part 4 is about your company’s knowledge production activities.

Please take your time but try not to linger on any one question; your first response to the question is usually your true belief. Additionally, you should take the questionnaire only once. Thank you for taking time to complete this survey. Your answer is important to us.

Yours sincerely,

Plymouth University Business School
Drake Circus, Plymouth, Devon, UK PL4 8AA
Mr. Jiang Pan, PhD Researcher and Associate Lecturer
Email: jiang.pan@plymouth.ac.uk

Part 1. This part is about you and your company's profile information

Q1. We care about the quality of our survey data and hope to receive the most accurate measures of your opinions, so it is important to us that you thoughtfully provide your best answer to each question in the survey.

Do you commit to providing your thoughtful and honest answers to the questions in this survey?

- ○ I will provide my best answers
- ○ I will not provide my best answers
- ○ I can't promise either way

Condition: I will provide my best answers is Not Selected. Skip to: End of Block

Q2. What type of industry does your company belong to?

- ○ Manufacturing
- ○ Agriculture
- ○ Financial Services
- ○ Software
- ○ Other

Condition: Manufacturing is Not Selected. Skip To: End of Block

Q3. Your company's business nature

- ○ Machinery & Electronics Manufacturing
- ○ Food & Drink
- ○ Other

Condition: Other is Selected. Skip To: End of Block

Q4. Do you have any experience in using enterprise resource planning system (ERP), material requirements planning system (MRP) or other information systems to manage business data and information in your company?

- Yes
- No

Condition: No is Selected. Skip To: End of Block

Q5. Number of employees

- < 50
- 51-250
- 251-500
- > 500

Q6. Respondent position

- Top management (chief executive, owner, director, etc.)
- Senior management (senior manager and departmental manager)
- Middle management (assistant manager, officer, etc.)
- Other

Condition: Other is Selected. Skip To: End of Block

Q7. Which country is your company located in?

- UK
- United States
- China

Part 2. The non-value adding activities in knowledge management that may exist in your company

*Please select one choice to indicate the extent to which you agree or disagree with each statement. The item scales are five-point Likert scales with 5=strongly disagree, 4=disagree, 3=neutral, 2=agree, 1=strongly agree

Q1. The following group of statements will ask you about situations caused by having too much potential suppliers' information regarding their credibility, price, product quality & features, production & delivery capability, etc.

When our company need to select suppliers in a short time….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1-.... we had too much different types of information from potential suppliers which are difficult to be evaluated and make a choice	○	○	○	○	○
2-.... we gathered too much information from potential suppliers, it greatly increased the workload in decision making.	○	○	○	○	○
3-.... we always feel stressful and exhausted to analyse all these information mentioned above from potential suppliers.	○	○	○	○	○

Q2. The following group of statements will ask you about situations caused by having too much market information regarding competitors, customers, distribution, sale personnel and market trends, etc.

When our company need to select a target market to get into in a short time….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1-.... we gathered too much different types of market information which are difficult to be analysed and make a choice	○	○	○	○	○
2-.... we gathered and analysed too much market information, and it confused our judgement.	○	○	○	○	○
3-.... we always feel stressful and exhausted to analyse all these information mentioned above from a market.	○	○	○	○	○

Q3. The following group of statements will ask you about situations caused by having too much internal obsolete information in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We keep an ever-increasing archive of obsolete information in company's database, it takes a great effort to maintain and use it.	○	○	○	○	○
2- It takes long time to find useful information in our database which is stacked with a large amount of obsolete information.	○	○	○	○	○
3- Our database is messed up by outdated and duplicated documents.	○	○	○	○	○

Q4. The following group of statements will ask you about situations caused by incompatibility of information systems (e.g. ERP, MRP, decision support system, customer relationship management system, etc.) in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Our new information systems are incompatible with the firm's old IT infrastructure.	○	○	○	○	○
2- The data and their format in the old information system do not match the requirement of the new information systems.	○	○	○	○	○
3- The new information system cannot read and store the data from the old information system automatically.	○	○	○	○	○

Q5. The following group of statements will ask you about situations caused by lack of extended enterprise functionality in your company's information systems (e.g. ERP, MRP, decision support system, customer relationship management system, etc.).

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Our information systems cannot interconnect with our business partners' information system	○	○	○	○	○
2- We have data inconsistency problems with our business partners.	○	○	○	○	○
3- Our information systems do not support the real-time sharing of information among our trading partners	○	○	○	○	○

Q6. The following group of statements will ask you about situations caused by inflexible information systems (e.g. ERP, MRP, decision support system, customer relationship management system, etc.) in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Our information systems are not easy to adapt to changes in processes regarding how we do our work.	○	○	○	○	○
2- Our information systems are not easy to adapt to changes in different collaboration modes with our business partners.	○	○	○	○	○
GI- Our information systems are not flexible to accommodate any change in our business operation.	○	○	○	○	○

Q7. The following group of statements will ask you about situations caused by cultural problems of the information systems (e.g. ERP, MRP, decision support system, customer relationship management system, etc.) in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- The language shown in our information systems are not accurately translated	○	○	○	○	○
2- The formats of tables and reports generated by our information systems do not meet the local government and business partners' requirement.	○	○	○	○	○
GI- The information systems used in our company are not localized enough.	○	○	○	○	○

Q8. The following group of statements will ask you about situations caused by low quality information from downstream of your company's supply chain (e.g. market, customers and competitors).

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- The data and information we get from the downstream of our supply chain is inaccurate.	○	○	○	○	○
2- We can't use the downstream data without adapting data code or entering it manually into information management system.	○	○	○	○	○
3- The downstream data and information we get is not reliable (e.g. demand forecast information keep changing)	○	○	○	○	○
4- The downstream data and information we get is untimely.	○	○	○	○	○
GI- The quality of the information we get from the downstream of our supply chain is poor	○	○	○	○	○

Q9. The following group of statements will ask you about situations caused by low quality information from your company's suppliers.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- The data and information we get from our suppliers is inaccurate.	○	○	○	○	○
2- We can't use the data from suppliers without adapting data code or entering it manually into Information management system.	○	○	○	○	○
3- The data and information we get from suppliers is not reliable. (i.e. the information keeps changing)	○	○	○	○	○
4- The data and information we get from suppliers is untimely.	○	○	○	○	○
GI- The quality of the information we get from the upstream of our supply chain is poor.	○	○	○	○	○

Q10. The following group of statements will ask you about the situation of your company's interactional knowledge inventory.

Our company have very little knowledge in….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- .... negotiating with trading partners	○	○	○	○	○
2- .... planning and management of partnering activities	○	○	○	○	○
3- .... using computers to network and communicate with partners	○	○	○	○	○
4- .... managing conflict with partners	○	○	○	○	○
GI- We have very little knowledge and experience in effectively interacting with trading partners.	○	○	○	○	○

Q11. The following group of statements will ask you about the situation of your company's functional knowledge inventory.

Our company have very little knowledge in….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- .... cost-reduction strategies involving suppliers	○	○	○	○	○
2- .... working with suppliers to develop products	○	○	○	○	○
3- .... working with suppliers to reduce delivery times	○	○	○	○	○
4- .... working with suppliers on quality management	○	○	○	○	○
GI- We have very little knowledge and experience in effectively working with supplier in production.	○	○	○	○	○

Q12. The following group of statements will ask you about the situation of your company's environmental knowledge inventory.

Our company have very little knowledge in….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- .... laws and regulations relevant to business partner relationships.	○	○	○	○	○
2- .... market conditions affecting buying and selling.	○	○	○	○	○
3- .... labour conditions in supplier firms	○	○	○	○	○
4- .... competitors' purchasing and selling behaviours.	○	○	○	○	○
GI- We have very little outside information and knowledge which could affect our business	○	○	○	○	○

Part 3. The value adding activities in knowledge management that may exist in your company

*Please select one choice to indicate the extent to which you agree or disagree with each statement. The item scales are five-point Likert scales with 5=strongly disagree, 4=disagree, 3=neutral, 2=agree, 1=strongly agree

Q1. The following group of statements will ask you about the situation of using relevant information & knowledge in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We can always locate, use and share the most relevant information and knowledge in our work.	○	○	○	○	○
2- We can always locate, use and share task-related information and knowledge for daily operations.	○	○	○	○	○
3- We can always locate, use and share the most relevant information and knowledge for decision making, planning, problem solving, and product development, etc.	○	○	○	○	○

Q2. The following group of statements will ask you about the situation of using timely and accurate data & information in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Data and information exchange between our trading partners and us is timely and accurate.	○	○	○	○	○
2- We can always get correct data and information when we need it.	○	○	○	○	○
3- Supply and demand information shared among our supply chain members is in an agreed time and error-free.	○	○	○	○	○

Q3. The following group of statements will ask you about the situation of possessing scarce information & knowledge in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We have the knowledge that gives us cutting-edge advantages in competition.	○	○	○	○	○
2- We have the knowledge that is costly to get for our competitors.	○	○	○	○	○
3- We have the knowledge that we keen to protect from our competitors.	○	○	○	○	○

Q4. The following group of statements will ask you about accessibility of data & information between your company and its business partners.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- The required data & information shared and stored in our supply chain is easy to find and use.	○	○	○	○	○
2- The required data & information shared and stored in our supply chain is in a right format for information management system to process.	○	○	○	○	○
3- The required data & information shared and stored in supply chain is understandable and readable for both information management system and users.	○	○	○	○	○

Q5. The following group of statements will ask you about the situation of trustful environment within your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- I can trust the people I work with to lend me a hand if I need it.	○	○	○	○	○
2- Most of my colleagues can be relied upon to do as they say they will do.	○	○	○	○	○
3- I feel quite confident that the firm will always try to treat me fairly.	○	○	○	○	○
4- I believe sharing knowledge with my colleagues can achieve mutual benefit rather than losing my power and knowledge advantage.	○	○	○	○	○
GI- I trust my colleagues	○	○	○	○	○

Q6. The following group of statements will ask you about the situation of trustful relationship with your company's business partners.

We and our trading partners….

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- .... can influence each other's business decisions.	○	○	○	○	○
2- .... have a mutual commitment to continue the partnership.	○	○	○	○	○
3- .... have a high degree of understanding about protecting exchanged business information.	○	○	○	○	○
4- .... have a high degree of smoothly coordinated business activity.	○	○	○	○	○
5- .... keep each other informed about events or changes that may affect each other's business.	○	○	○	○	○
GI- Our company and trading partners trust each other.	○	○	○	○	○

Q7. The following group of statements will ask you about the situation of using shared language in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We use common terms or jargon to communicate with our business partners and employees.	○	○	○	○	○
2- We use understandable communication pattern during the discussion.	○	○	○	○	○
3- We use understandable narrative forms to post messages or articles.	○	○	○	○	○

Q8. The following group of statements will ask you about the circumstance of the communication channel between your company and its business partners.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Except using traditional ways (e.g. email, fax, calls or face-to-face), we also use other modern software or apps (e.g. whatsapp and Skype, WeChat, etc.) to communication with our trading partners and employees.	○	○	○	○	○
2- We create many opportunities to make sure that communications within and outside of our company are regularly and frequently.	○	○	○	○	○
3- Communication Channels are open in our supply chain.	○	○	○	○	○

Part 4. Your company's knowledge production activities

*Please select one choice to indicate the extent to which you agree or disagree with each statement. The item scales are five-point Likert scales with 1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree.

Q1. The following group of statements will ask you about knowledge acquisition activities in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We can effectively acquire crucial information and knowledge from our business partners.	○	○	○	○	○
2- Required data and information can be transferred frequently and timely between our company and trading partners.	○	○	○	○	○
3- We often acquire critical information and knowledge through external survey or external knowledge-rich companies.	○	○	○	○	○
4- The data and information we got from outside of our company is understandable and usable	○	○	○	○	○

Q2. The following group of statements will ask you about knowledge selection activities in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We can easily find the most relevant information or documents in our database when we need them.	○	○	○	○	○
2- We are able to locate and assign employees who have right skills or knowledge to complete specific tasks (decision making, product development, problem solving, etc.).	○	○	○	○	○
3- We are able to find suitable person in our company to train other employees.	○	○	○	○	○
GI- We can always find right information and knowledge inside our company to solve problems.	○	○	○	○	○

Q3. The following group of statements will ask you about knowledge generation activities in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- Our company are able to make accurate supplier selection decisions within a short time.	○	○	○	○	○
2- Our company are able to accurately target a market within a short time.	○	○	○	○	○
3- The report generated from our information management system is fully understandable and its format can meet government and business partners' requirement.	○	○	○	○	○
4- We can adjust our business processes plans (day-to-day operations) without any technical constrain from our information management system.	○	○	○	○	○
5- We can adjust our partner-style with different suppliers easily and effectively.	○	○	○	○	○
6- We have accurate plans for allocating the short and long-term capacity (good equipment and labour utilisation).	○	○	○	○	○
7- We are able to adjust our marketing strategies successfully.	○	○	○	○	○
8- We have efficient inventory strategies.	○	○	○	○	○
9- We have successful strategies for keeping reliable partnerships with our suppliers.	○	○	○	○	○
10- We can make effective conflict-solving strategies for working with our business partners.	○	○	○	○	○
11- We have effective cost-reduction strategies with suppliers.	○	○	○	○	○
GI- We can always make effective decision and plans for our business operation.	○	○	○	○	○

Q4. The following group of statements will ask you about knowledge internalization activities in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- The data, reports and documents can be transferred and stored smoothly in our company's computers without any technological limit.	○	○	○	○	○
2- Our database is well organised, every piece of information or documents are indexed based on its character and expected purpose.	○	○	○	○	○
3- Information and knowledge sharing is openly and frequently among our employees.	○	○	○	○	○
4- Peer learning in our company is effectively and efficiently.	○	○	○	○	○
GI- We can always utilize information and knowledge effectively and efficiently in our company.	○	○	○	○	○

Q5. The following group of statements will ask you about knowledge externalisation activities in your company.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1- We are able to launch competitive products and services in the market.					
2- We have many successful product co-development experiences with our business partners					
3- We are able to work with business partners to reduce delivery times effectively.					
4- We have many successful experiences of working with business partners on product quality management.					
GI- Our products and services are successful in the market.					

Consent Form

What is this project about?

This project primarily explores the relationships between value-adding factors, non-value adding factors, and knowledge management processes (KMPs) in the manufacturing supply chain (MSC) context. This study may reveal how to enhance a MSC's knowledge management performance by eliminating the non-value adding factors in KMPs and using value-adding principles as guidance to effectively manage KMPs' activities.

Who are we?

This project is undertaken by Jiang Pan, a PhD student with Business School of Plymouth University. The supervisors are Prof. Shaofeng Liu and Dr. Sarah Tuck.

Confidentiality

Research will maintain the anonymity of participants and the confidentiality of the information that they supply in order to protect their privacy. All survey information collected for the research will be treated confidentially. Published work will always anonymise any responses and never identify the source. If required, researcher would obtain the authority before publishing any participant's company specific details.

Right to withdraw

Participation is voluntary, and you have the right to withdraw from the study before 01/12/2018. Please note that after the date given above, we will not be able to withdraw the data as a substantial amount of data analysis work would have been done.

Feedback

You may obtain information on the project progress or a summary of the findings of the research by contacting: jiang.pan@plymouth.ac.uk.

Thank you in advance for your interest and assistance with this research.

Appendix C: Questionnaire (Chinese Version)

关于生产性行业的信息知识管理绩效调查

尊敬的女士/先生

您好！我是一名在英国普利茅斯大学运营与供应链管理学院就读的博士生。现在正在为我的研究课题“如何运用精益理论改善生产性行业中的信息知识管理水平”进行问卷调查。希望占用您宝贵的 15 至 17 分钟时间。此问卷共四个部分，第一部分是关于您及您公司的概况信息；第二部分是关于本公司在信息、知识管理中可能存在的一些不合理因素；第三部分是关于本公司在信息、知识管理中存在的有效因素。最后一部分是关于本公司信息知识管理的整体状况。

我们保证您的回答是匿名保密的，所有信息只用于学术研究。另外，如有不便您可以在任何时候放弃回答问卷。 您的回答对我们非常宝贵，感谢您的帮助!

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第一部分: 您与您所在公司的基本信息

Q1. 您的经验知识对我们非常宝贵，因此您所作出的每个回答将对我们的研究起到至关重要的影响。

您能够保证所做作出的回答是认真并且经过深思熟虑的吗？

- 我将保证会给出我最好的回答
- 我不会给出我最好的回答
- 我不会予以作答

Condition: I will provide my best answers is Not Selected. Skip to: End of Block

Q2. 您所在的公司属于以下哪个行业？

- 生产业
- 农业
- 金融业
- 软件开发
- 其他

Condition: Manufacturing is Not Selected. Skip To: End of Block

Q3. 公司行业领域：

- 机械、电子制造类
- 食品、饮料业
- 其他

Condition: Other is Selected. Skip To: End of Block

Q4. 在您的公司里您有过使用信息管理系统（如：ERP，MRP，或客户关系管理系统，等等）来管理商业运营数据和信息的经验吗？

- ○ 有
- ○ 没有

Condition: No is Selected. Skip To: End of Block

Q5. 公司的员工数量：

- ○ < 50 人
- ○ 51-250 人
- ○ 251-500 人
- ○ > 500 人

Q6. 您在公司的职位。

- ○ 最高决策层
- ○ 高层管理者
- ○ 中层管理者
- ○ 其他

Condition: Other is Selected. Skip To: End of Block

Q7. 您的公司位于哪个国家。

- ○ 英国
- ○ 美国
- ○ 中国

第二部分：关于本公司在信息、知识管理中可能存在的一些负面因素

*请按照您公司实际情况在以下陈述中对于不同的赞同程度做出选择。

Q1. 下列叙述是关于：当公司需要在很短时间内选择合适的供应商时，由于收集了过多有关潜在供应商们的信息（如：信誉，产品特性和质量，价格，生产和派送能力等）对公司决策所造成的影响。

	完全不同意	不同意	中立	同意	完全同意
1. 我们经常收集太多潜在供应商们的不同类型的信息，这导致我们很难对他们进行评估和作出选择	○	○	○	○	○
2. 我们从潜在供应商们那里收集了太多信息，这大大增加了我们作抉择的工作量。	○	○	○	○	○
3. 我们总是分析来自潜在供应商们的所有信息，这使得工作压力很大。	○	○	○	○	○

Q2. 下列叙述是关于：当公司需要在很短时间内选择目标市场时，由于收集了过多市场信息（如：竞争对手，客户，派送运输，销售人员，市场趋势等）对公司决策所造成的影响。

	完全不同意	不同意	中立	同意	完全同意
1.我们经常收集太多有关目标市场不同类型的信息，这导致我们很难对它们进行评估并作出决定。	○	○	○	○	○
2. 我们总是从潜在目标市场那里收集太多信息，这大大增加了我们做抉择的工作量。	○	○	○	○	○
3. 我们总是分析所有潜在目标市场的信息，这使得感到工作负担很重。	○	○	○	○	○

Q3. 下列叙述是关于：由于您的公司保留太多过时/过期的信息资料、文件所可能导致的问题。

	完全不同意	不同意	中立	同意	完全同意
1. 我们在公司资料库中保存的过期信息资料不断增长，这使我们额外付出很多劳力去维护和使用我们的资料库。	○	○	○	○	○
2. 我们的资料库堆积了大量过期没用的资料文件，这使我们要花很长时间才能找到有用信息。	○	○	○	○	○
3. 我们的资料库被过期和重复的文件搞得很乱。	○	○	○	○	○

Q4. 下列叙述是关于：您公司里的信息管理系统（如：ERP，MRP，决策支持系统，或者客户关系管理系统等等）与公司里的老系统不兼容所导致的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们公司的新信息管理系统与公司内已有的 IT 基础硬件设备不相兼容。	○	○	○	○	○
2. 公司里旧系统里的数据和格式与新系统不匹配。	○	○	○	○	○
3. 公司的新信息管理系统不能读取和储存旧系统中的数据信息。	○	○	○	○	○

Q5. 下列叙述关于：由于公司的信息系统与业务合作伙伴（供应商和客户）的系统缺少实时信息交流功能所导致的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们的信息管理系统不能跟业务合作伙伴的信息管理系统互联。	○	○	○	○	○
2. 我们与业务合作伙伴有信息数据不一致的问题。	○	○	○	○	○
3. 我们的信息系统不支持与业务合作伙伴之间进行实时信息分享。	○	○	○	○	○

Q6. 下列陈述关于：公司信息数据管理系统在公司运营管理流程上缺乏灵活性可能导致的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 公司的信息数据管理系统有固定的工作流程，不能根据我们日常工作需要而做出相应改变。	○	○	○	○	○
2. 我们的信息数据管理系统中的工作流程不能根据我们与业务合作伙伴的不同合作形式而做出相应调整。	○	○	○	○	○
GI-我们的信息数据管理系统不能足够灵活地适应我们业务运营中的任何改变。	○	○	○	○	○

Q7. 下列叙述是有关运用国外信息管理系统（如：ERP, MRP, 决策支持系统, 客户关系管理系统等....）可能遇到的文化问题。

	完全不同意	不同意	中立	同意	完全同意
1. 我们信息管理系统里所用的语言、词语没有被准确翻译过来。	○	○	○	○	○
2. 公司信息管理系统所做的表格和报告的格式不符合政府和业务合作伙伴的要求。	○	○	○	○	○
GI-我们公司使用的信息系统尚未本地化。	○	○	○	○	○

Q8. 下列叙述是关于：由于来自供应链下游（市场，客户，竞争对手）的信息质量低下所出现的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们从供应链下游得到的信息和数据不准确。	○	○	○	○	○
2. 对于那些来自供应链下游的数据，我们必须对它们重新编码或者手动输入进我们的信息管理系统，否则无法使用。	○	○	○	○	○
3. 我们获得的供应链下游信息不可靠（这些信息总是不停的变动，我们无法依照它们做决策）。	○	○	○	○	○
4. 我们总是不能及时获得供应链下游信息。	○	○	○	○	○
GI-我们无法从供应链下游获得质量可靠的信息。	○	○	○	○	○

Q9. 下列叙述是关于：由于来自供应商的信息质量低下所出现的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们从供应商那里得到的信息和数据不准确。	○	○	○	○	○
2. 对于那些供应商传来的信息数据，我们必须对它们重新编码或者手动输入进我们的信息管理系统，否则无法使用。	○	○	○	○	○
3. 供应商传给我们的信息不可靠（这些信息总是不停的变动，我们无法依照它们做决策）	○	○	○	○	○
4. 我们总是无法及时从供应商那里获得所需的信息。	○	○	○	○	○
GI-我们无法从供应链上游获得质量可靠的信息。	○	○	○	○	○

Q10. 下列叙述是关于您公司与业务合作伙伴互动所需的经验知识储备情况。

	完全不同意	不同意	中立	同意	完全同意
1. 在与业务合作伙伴谈判、交涉方面，我们的经验知识不足。	○	○	○	○	○
2. 在策划和管理合作事务方面，我们的经验知识不足。	○	○	○	○	○
3. 在运用电脑与合作伙伴联络和交流方面，我们的知识经验不足。	○	○	○	○	○
4. 在管理掌控跟合作伙伴之间的矛盾分歧方面，我们的知识经验不足。	○	○	○	○	○
GI-我们对与贸易合作伙伴进行有效互动的知识经验掌握的很少。	○	○	○	○	○

Q11. 下列叙述是关于您公司与供应商合作需要的功能性的经验知识储备情况。

	完全不同意	不同意	中立	同意	完全同意
1. 在与供应商们合作来降低成本方面，我们的经验知识不足。	◯	◯	◯	◯	◯
2. 在与供应商合作共同开发产品方面，我们的经验知识不足。	◯	◯	◯	◯	◯
3. 在与供应商合作来缩短交货时间方面，我们的经验知识不足。	◯	◯	◯	◯	◯
4. 在与供应商合作来提高质量管理水平方面，我们的经验知识不足。	◯	◯	◯	◯	◯
GI- 在与供应商合作来提高生产质量和水平等方面，我们的经验知识不足。	◯	◯	◯	◯	◯

Q12. 下列叙述是关于你公司对商业环境的知识经验储备的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 在商业合作事务相关的法律法规方面，我们的经验知识不足。	○	○	○	○	○
2. 在那些会影响我们采购和销售的市场行情方面，我们的经验知识不足。	○	○	○	○	○
3. 我们对供应商的劳工条件和状况了解的不足。	○	○	○	○	○
4. 我们对竞争对手的采购和销售情况了解不足。	○	○	○	○	○
GI- 关于那些会影响我们企业运行的外部信息和知识我们掌握的还不充足。	○	○	○	○	○

第三部分：关于本公司在信息、知识管理中可能存在的正面因素。

*请按照您公司实际情况在以下叙述中对于不同的赞同程度做出选择。

Q1. 下列叙述是关于您公司对目的明确的知识信息（以特定工作任务为导向的信息）的使用情况。

	完全不同意	不同意	中立	同意	完全同意
1. 在日常工作中我们总能找出、使用并且共享最相关贴切的知识信息。	○	○	○	○	○
2. 我们总能找到，使用和共享以我们工作任务相关的知识信息。	○	○	○	○	○
3. 我们总是能找到、使用并且共享最相关的知识和信息来进行决策制定，规划，解决问题和产品开发等工作任务。	○	○	○	○	○

Q2. 下列叙述是关于您的公司在运用准确、及时的信息方面的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们与业务合作伙伴间交流的信息非常及时准确。	○	○	○	○	○
2. 在我们需要时我们总能从合作伙伴那里得到准确的数据信息。	○	○	○	○	○
3. 公司供应链成员间能够在协定的时间内准确无误的交流供需信息。	○	○	○	○	○

Q3. 下列叙述关于您公司是否掌握稀有信息、经验或技术的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们掌握能在市场竞争中给我们绝对优势的知识或技术。	○	○	○	○	○
2. 我们拥有那些对我们的竞争对手来说要花很大代价才能获得的技术知识。	○	○	○	○	○
3. 我们拥有那种要对竞争对手绝对保密的技术知识。	○	○	○	○	○

Q4. 下列叙述关于您公司与业务合作伙伴间的信息通畅性的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们可以根据需要很容易的找到并使用那些在供应链成员间所保存和共享的信息。	○	○	○	○	○
2. 在我们的供应链中，信息数据都是以合适的、正确的格式分享和保存以便成员们的信息系统处理使用。	○	○	○	○	○
3. 我们供应链成员间所保存和共享的信息对于使用者和信息管理系统都是易读易懂的。	○	○	○	○	○

Q5. 下列叙述是有关公司内互信的工作环境的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 工作上，我相信在我有需要的时候同事们会给我帮助。	○	○	○	○	○
2. 公司里的大部分同事都能言行一致，说到做到。	○	○	○	○	○
3. 无论是在酬劳上还是任用上，我相信公司会对我很公平。	○	○	○	○	○
4. 我相信与同事分享业务经验或知识将会是互惠双赢的事情，这不会导致我在公司里失去原有地位和知识优势。	○	○	○	○	○
GI- 我相信我的同事。	○	○	○	○	○

Q6. 下列叙述是关于你公司与业务合作伙伴互信关系的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们与合作伙伴可以相互影响对方的商业决策。	○	○	○	○	○
2. 我们与商业伙伴有相互承诺将我们的合作关系继续下去。	○	○	○	○	○
3. 对于保护双方交流的商业信息的重要性，我们与业务伙伴有高度的认识。	○	○	○	○	○
4. 在业务活动方面，我们与业务合作伙伴有很高程度的协调性。	○	○	○	○	○
5. 我们与商业伙伴对那些可能会影响到对方生意的变动或事件会相互通知提醒。	○	○	○	○	○
GI- 我们公司与合作伙伴之间有良好的互信关系。	○	○	○	○	○

Q7. 下列叙述是关于您公司在使用“共同语言”方面的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们用通用易懂的术语或行话与员工和商业伙伴交流。	○	○	○	○	○
2. 在商讨中我们交流形式易懂有效。	○	○	○	○	○
3. 我们在发信件或刊登文章时使用的叙述形式简单易懂。	○	○	○	○	○

Q8. 下列叙述是有关您公司与业务合作伙伴的信息沟通渠道的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 除了用较传统的方式（如：email, 传真，电话或面对面形式的）， 我们也用更现代的软件 app（如：QQ，微信，Skype，What-app 等）与我们的商业伙伴和员工进行交流。	○	○	○	○	○
2. 我们创造了很多机会以确保公司内外定期、频繁的的进行信息交流。	○	○	○	○	○
3. 我们供应链成员间的沟通渠道始终是开放的。	○	○	○	○	○

第四部分：关于本公司在信息和知识管理的表现情况。

*请按照您公司实际情况在以下叙述中对于不同的赞同程度做出选择。

Q1. 下列叙述关于您公司在从外界获取信息知识方面的表现。

	完全不同意	不同意	中立	同意	完全同意
1. 我们可以很有效的从公司的合作伙伴那里获取重要的信息和知识。	○	○	○	○	○
2. 我们和合作伙伴双方所需的数据信息可以进行频繁及时的交流共享。	○	○	○	○	○
3. 我们经常通过公司外部调查或者从具备丰富知识的公司那里获得关键信息和知识。	○	○	○	○	○
4. 我们从公司外部获得的那些信息知识是易懂和容易使用的。	○	○	○	○	○

Q2. 下列叙述是有关您公司知识选择的表现。

	完全不同意	不同意	中立	同意	完全同意
1. 我们可以很轻松的在公司的数据库中找到所需的信息资料来完成工作任务。	○	○	○	○	○
2. 我们能够找到并指派具有正确技能或知识经验的员工完成相应的任务（如：决策制定，产品开发，问题处理等）。	○	○	○	○	○
3. 我们能够在公司里找到合适的员工来培训其他员工。	○	○	○	○	○
GI- 我们总是可以在公司内部找到正确的信息和知识来解决面临的问题。	○	○	○	○	○

Q3. 下列叙述是关于您公司在知识创造方面的表现。

	完全不同意	不同意	中立	同意	完全同意
1. 我们可以在有限的时间内做出准确的供应商选择决策。	○	○	○	○	○
2. 我们可以在很短时间内对目标市场做出准确选择。	○	○	○	○	○
3. 我们公司的信息管理系统做出的报告是易懂的，其格式也完全符合政府和业务合作伙伴的要求。	○	○	○	○	○
4. 我们可以不受信息管理系统的限制按需要调整业务工作流程。	○	○	○	○	○
5. 我们可以轻松有效地调整跟不同供应商的合作方式。	○	○	○	○	○
6. 我们可以准确制定计划来分配长期和短期的生产力（高效的设备和人工利用率）。	○	○	○	○	○
7. 我们有能力成功调整市场行销策略。	○	○	○	○	○
8. 我们有高效的库存管理策略。	○	○	○	○	○
9. 我们有成功的策略来保持与供应商的可靠合作关系。	○	○	○	○	○

10. 为了与商业伙伴更好的合作，我们能针对矛盾冲突制定出有效解决策略。	○	○	○	○	○
11. 我们有与供应商合作有效削减成本的策略。	○	○	○	○	○
GI-我们始终可以为我们的业务运营制定有效的决策和计划。	○	○	○	○	○

Q4. 下列叙述是关于在您公司里的知识内化方面的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 数据、报告和文件可以在公司的计算机中顺利地传输和储存，没有任何技术障碍。	◯	◯	◯	◯	◯
2. 我们有管理完善的数据库，每一条信息或文档都根据其特征和作用进了分类和索引。	◯	◯	◯	◯	◯
3. 在员工之间我们的信息和知识分享是频繁和公开的。	◯	◯	◯	◯	◯
4. 我们同事之间的相互学习非常有效。	◯	◯	◯	◯	◯
GI- 我们始终可以在公司中有效地利用信息和知识。	◯	◯	◯	◯	◯

Q5. 下列叙述是关于在您公司里的知识外化方面的情况。

	完全不同意	不同意	中立	同意	完全同意
1. 我们有能力在市场上推出有竞争力的产品和服务。	◯	◯	◯	◯	◯
2. 我们有很多与业务合作伙伴共同开发产品的成功经验。	◯	◯	◯	◯	◯
3. 我们能够与供应商合作有效地缩短交货时间。	◯	◯	◯	◯	◯
4. 在与商业伙伴合作提高产品质量方面，我们有很多成功经验。	◯	◯	◯	◯	◯
GI- 我们的产品和服务在市场上很成功。	◯	◯	◯	◯	◯

知情同意书

<u>项目简介</u>

该项目主要探索在制造业供应链（MSC）背景下的增值因素，非增值因素跟知识管理过程（KMPs）之间的关系。该项目可能会揭示如何通过消除KMPs中的非增值因素，并以精益生产中的正面增值原则作为指导来有效管理 KMPs 的活动，从而提高 MSC 的知识管理绩效。

<u>关于我们</u>

该项目由英国普利茅斯大学商学院博士生潘江进行，由 Shaofeng Liu 教授和 Sarah Tuck 博士作指导。

<u>保密细节</u>

研究将维护参与者的匿名性。为研究收集的所有调查数据将被保密处理。未来要发表的研究成果也不会公开信息来源。如果需要，研究人员将在得到参与人和公司的授权同意后才会发表其细节信息。

<u>撤回权</u>

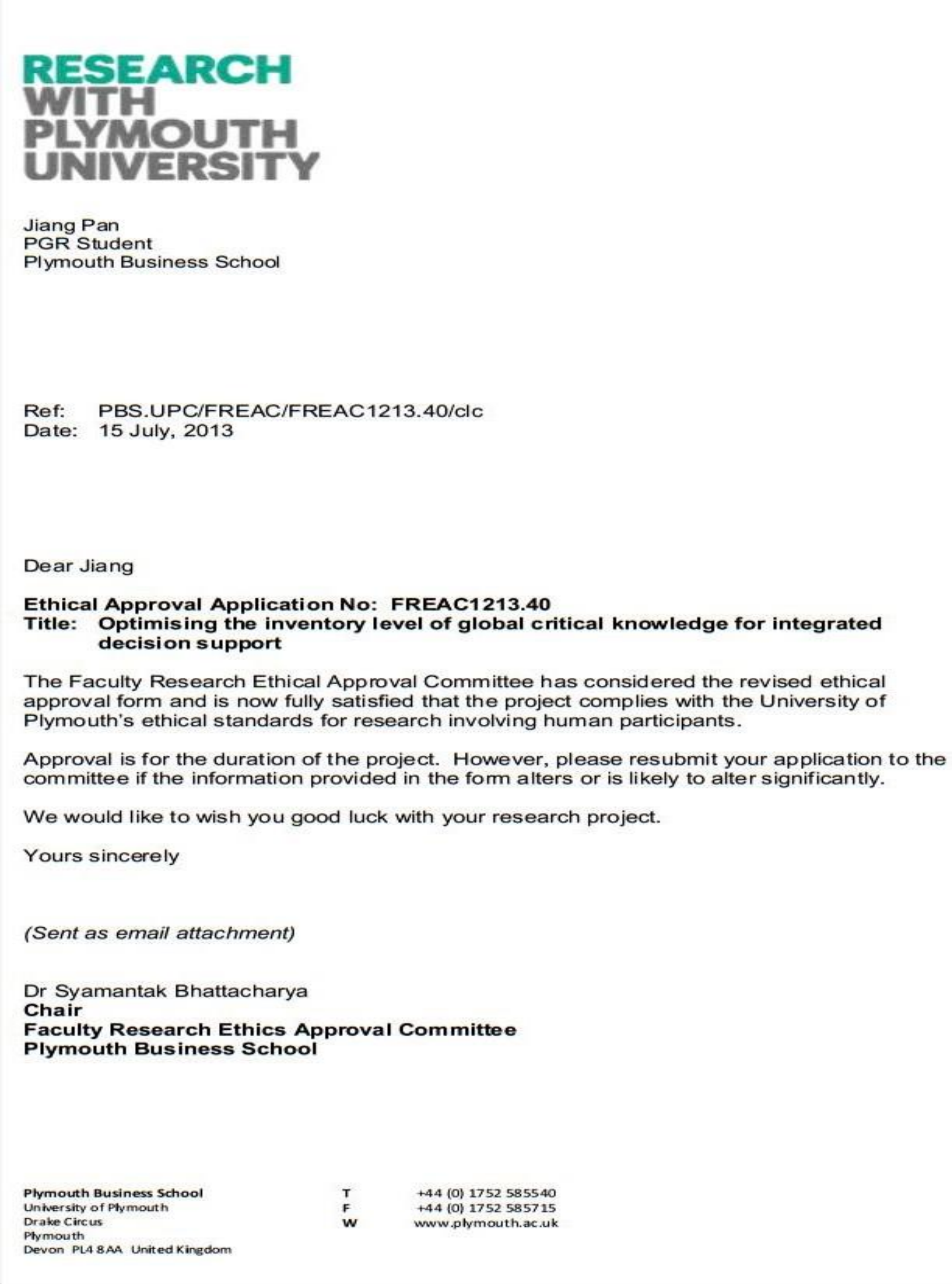
此次调查的参与是自愿的。您有权在2018年12月1日之前退出研究。请注意，在上述日期之后，我们将无法撤回数据，因为大量分析工作已经完成。

<u>反馈</u>

如果您对本研究感兴趣，您可以通过联系：jiang.pan@plymouth.ac.uk 获得关于项目进展的信息和研究结果摘要。

感谢你对本研究的参与和帮助。

Appendix D: Ethical Approval Form



RESEARCH WITH PLYMOUTH UNIVERSITY

Jiang Pan
PGR Student
Plymouth Business School

Ref: PBS.UPC/FREAC/FREAC1213.40/clc
Date: 15 July, 2013

Dear Jiang

Ethical Approval Application No: FREAC1213.40
Title: Optimising the inventory level of global critical knowledge for integrated decision support

The Faculty Research Ethical Approval Committee has considered the revised ethical approval form and is now fully satisfied that the project complies with the University of Plymouth's ethical standards for research involving human participants.

Approval is for the duration of the project. However, please resubmit your application to the committee if the information provided in the form alters or is likely to alter significantly.

We would like to wish you good luck with your research project.

Yours sincerely

(Sent as email attachment)

Dr Syamantak Bhattacharya
Chair
Faculty Research Ethics Approval Committee
Plymouth Business School

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Appendix E: Mahalanobis Distance Test

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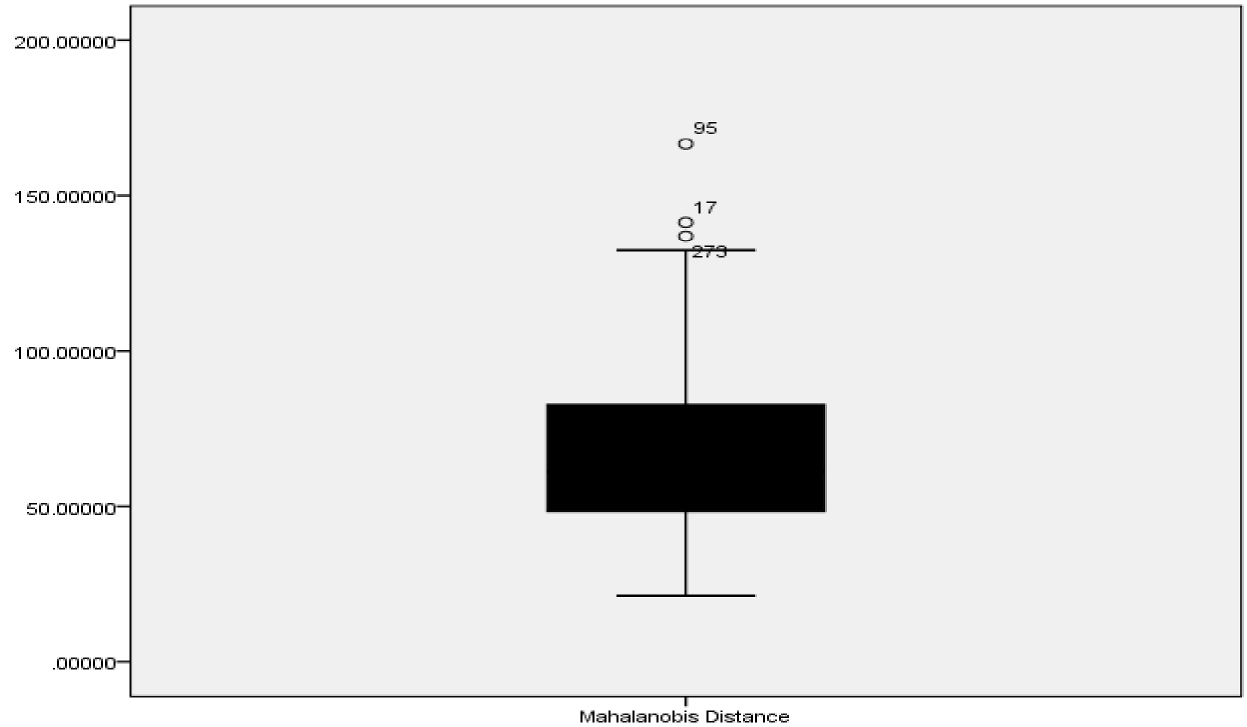
Mahalanobis Distance Stem-and-Leaf Plot

 Frequency    Stem &  Leaf

    18.00        2.  113334455555777888
    35.00        3.  00122222222223333344555667888888889999
    47.00        4.  00011122223334444444456666667777777788888899999999
    74.00        5.
00000000111111122222233333444445555555555556666667777778888888888889999
99999
    49.00        6.
0000111122222333344445555556677777788888888899999999
    34.00        7.  0011122333444455555567777888888999
    44.00        8.  00001112222223444445556666667777778889999999999
    26.00        9.  00011222344445555777888999
    15.00       10.  022333445678888
     8.00       11.  00014458
     4.00       12.  0248
     2.00       13.  02
     3.00 Extremes    (>=137)

 Stem width:  10.00000
 Each leaf:        1 case(s)
```



Appendix F: The Outer Loading of the Reflective Indicators

	ACCES	ECC	ILIO	INCOMPA	KA	LEEF	MIO	RELEV	SCAR	SIO	SL	T&A
acces_1	0.837											
acces_2	0.821											
acces_3	0.753											
ecc_1		0.592										
ecc_2		0.819										
ecc_3		0.8										
ilio_1			0.881									
ilio_2			0.927									
ilio_3			0.889									
incompa_1				0.905								
incompa_2				0.917								
incompa_3				0.894								
ka_1					0.88							
ka_2					0.866							
ka_3					0.845							
ka_4					0.842							
leef_1						0.821						
leef_2						0.849						
leef_3						0.852						
mio_1							0.878					
mio_2							0.906					
mio_3							0.883					
relev_1								0.863				
relev_2								0.819				
relev_3								0.793				
scar_1									0.825			
scar_2									0.746			
scar_3									0.724			
sio_1										0.899		
sio_2										0.89		
sio_3										0.881		
sl_1											0.693	
sl_2											0.642	
sl_3											0.803	
t&a_1												0.876
t&a_2												0.891
t&a_3												0.891

Notes: supplier information overload (SIO); market information overload (MIO); internal legacy information overload (ILIO); incompatibility (INCOMPA); lack of extended enterprise functionality (LEEF); relevancy (RELEV); timeliness & accuracy (T&A); scarcity (SCAR); accessibility (ACCES); shared language (SL); expanding communication channel (ECC); knowledge acquisition (KA).

Appendix G: The Cross-Loadings of the Reflective Indicators

	ACCES	ECC	ILIO	INCOMPA	KA	LEEF	MIO	RELEV	SCAR	SIO	SL	T&A
acces_1	0.837	0.533	-0.389	-0.408	0.387	-0.45	-0.263	0.601	0.558	-0.275	0.497	0.509
acces_2	0.821	0.497	-0.395	-0.413	0.363	-0.43	-0.284	0.571	0.529	-0.295	0.457	0.509
acces_3	0.753	0.485	-0.202	-0.185	0.087	-0.397	-0.082	0.52	0.489	-0.067	0.472	0.302
ecc_1	0.382	0.592	-0.286	-0.312	0.099	-0.348	-0.191	0.331	0.381	-0.192	0.405	0.219
ecc_2	0.549	0.819	-0.303	-0.27	0.235	-0.344	-0.166	0.449	0.478	-0.22	0.521	0.307
ecc_3	0.468	0.8	-0.214	-0.264	0.384	-0.255	-0.188	0.42	0.413	-0.224	0.482	0.391
ilio_1	-0.336	-0.297	0.881	0.624	-0.491	0.46	0.677	-0.189	-0.182	0.676	-0.261	-0.548
ilio_2	-0.394	-0.295	0.927	0.752	-0.612	0.512	0.763	-0.266	-0.306	0.752	-0.297	-0.658
ilio_3	-0.399	-0.327	0.889	0.707	-0.591	0.495	0.703	-0.264	-0.303	0.68	-0.259	-0.655
incompa_1	-0.382	-0.32	0.687	0.905	-0.623	0.451	0.696	-0.265	-0.318	0.699	-0.301	-0.6
incompa_2	-0.405	-0.345	0.718	0.917	-0.604	0.504	0.704	-0.291	-0.338	0.682	-0.339	-0.635
incompa_3	-0.381	-0.313	0.698	0.894	-0.579	0.478	0.697	-0.284	-0.323	0.65	-0.292	-0.608
ka_1	0.268	0.31	-0.546	-0.582	0.88	-0.169	-0.601	0.211	0.31	-0.633	0.256	0.693
ka_2	0.354	0.3	-0.59	-0.607	0.866	-0.206	-0.586	0.228	0.31	-0.618	0.275	0.731
ka_3	0.381	0.321	-0.575	-0.601	0.845	-0.225	-0.561	0.225	0.332	-0.614	0.309	0.737
ka_4	0.249	0.295	-0.449	-0.493	0.842	-0.129	-0.51	0.179	0.237	-0.551	0.208	0.63
leef_1	-0.492	-0.361	0.46	0.458	-0.161	0.821	0.361	-0.377	-0.414	0.351	-0.418	-0.276
leef_2	-0.424	-0.322	0.448	0.43	-0.184	0.849	0.394	-0.361	-0.36	0.37	-0.369	-0.287
leef_3	-0.425	-0.326	0.465	0.442	-0.189	0.852	0.385	-0.354	-0.337	0.343	-0.339	-0.278
mio_1	-0.245	-0.243	0.679	0.654	-0.555	0.42	0.878	-0.161	-0.244	0.762	-0.275	-0.559
mio_2	-0.196	-0.166	0.723	0.706	-0.591	0.382	0.906	-0.136	-0.187	0.788	-0.196	-0.562
mio_3	-0.284	-0.22	0.718	0.698	-0.608	0.405	0.883	-0.151	-0.221	0.793	-0.229	-0.63
relev_1	0.582	0.447	-0.25	-0.286	0.261	-0.349	-0.163	0.863	0.518	-0.156	0.452	0.339
relev_2	0.547	0.399	-0.221	-0.271	0.224	-0.335	-0.173	0.819	0.458	-0.146	0.408	0.369
relev_3	0.612	0.491	-0.188	-0.207	0.119	-0.388	-0.078	0.793	0.503	-0.069	0.505	0.311
scar_1	0.584	0.522	-0.33	-0.397	0.389	-0.379	-0.282	0.521	0.825	-0.3	0.456	0.512
scar_2	0.463	0.394	-0.169	-0.204	0.122	-0.323	-0.1	0.428	0.746	-0.14	0.37	0.251
scar_3	0.438	0.352	-0.144	-0.187	0.243	-0.298	-0.148	0.412	0.724	-0.185	0.323	0.299
sio_1	-0.258	-0.243	0.697	0.66	-0.637	0.392	0.785	-0.162	-0.262	0.899	-0.259	-0.61
sio_2	-0.21	-0.234	0.703	0.643	-0.614	0.335	0.783	-0.09	-0.219	0.89	-0.218	-0.582
sio_3	-0.272	-0.277	0.689	0.694	-0.628	0.398	0.777	-0.151	-0.275	0.881	-0.209	-0.62
sl_1	0.427	0.399	-0.222	-0.297	0.222	-0.322	-0.181	0.348	0.375	-0.185	0.693	0.289
sl_2	0.41	0.448	-0.134	-0.158	0.123	-0.341	-0.102	0.426	0.392	-0.084	0.642	0.157
sl_3	0.437	0.494	-0.282	-0.283	0.293	-0.305	-0.261	0.41	0.34	-0.263	0.803	0.323
t&a_1	0.439	0.301	-0.607	-0.607	0.74	-0.258	-0.629	0.311	0.365	-0.625	0.266	0.876
t&a_2	0.509	0.412	-0.594	-0.573	0.713	-0.304	-0.548	0.402	0.461	-0.566	0.337	0.891
t&a_3	0.531	0.414	-0.635	-0.624	0.711	-0.323	-0.574	0.377	0.451	-0.616	0.354	0.891

Notes: supplier information overload (SIO); market information overload (MIO); internal legacy information overload (ILIO); incompatibility (INCOMPA); lack of extended enterprise functionality (LEEF); relevancy (RELEV); timeliness & accuracy (T&A); scarcity (SCAR); accessibility (ACCES); shared language (SL); expanding communication channel (ECC); knowledge acquisition (KA).

Appendix H: The Fornell-Larcker Criterion

	ACCES	CM	ECC	ILIO	INCOMPA	INFLEX	KA	KE	KG	KI	KS	LEEF	LEKI	LFKI	LIKI	LQDI	LQUI	MIO	RELEV	SCAR	SIO	SL	T&A	TEO	TRP
ACCES	0.804																								
CM	-0.245																								
ECC	0.627	-0.187	0.744																						
ILIO	-0.419	0.564	-0.34	0.899																					
INCOMPA	-0.43	0.611	-0.36	0.774	0.906																				
INFLEX	-0.427	0.648	-0.35	0.689	0.742																				
KA	0.364	-0.646	0.357	-0.629	-0.665	-0.709	0.858																		
KE	0.09	0.121	0.084	0.281	0.218	0.27	-0.174																		
KG	-0.142	0.413	-0.125	0.534	0.517	0.586	-0.598	0.779																	
KI	0.625	-0.48	0.62	-0.592	-0.634	-0.651	0.746	-0.069	-0.44																
KS	0.52	-0.541	0.459	-0.411	-0.463	-0.576	0.69	0.003	-0.329	0.732															
LEEF	-0.53	0.302	-0.399	0.544	0.527	0.462	-0.212	0.028	0.118	-0.382	-0.294	0.841													
LEKI	-0.024	0.062	-0.032	-0.205	-0.146	-0.191	0.178	-0.752	-0.709	0.158	0.012	0.019													
LFKI	-0.051	0.052	-0.079	-0.128	-0.134	-0.162	0.133	-0.761	-0.682	0.065	-0.025	0.052	0.869												
LIKI	0.018	0.068	-0.028	-0.144	-0.142	-0.162	0.168	-0.753	-0.693	0.163	0.042	0.001	0.845	0.831											
LQDI	-0.108	0.094	-0.087	-0.064	-0.03	-0.084	0.136	-0.761	-0.685	0.073	-0.026	0.16	0.774	0.775	0.799										
LQUI	-0.116	0.121	-0.114	-0.048	-0.005	-0.03	0.119	-0.767	-0.675	0.021	-0.035	0.193	0.766	0.781	0.783	0.856									
MIO	-0.272	0.641	-0.236	0.795	0.772	0.67	-0.658	0.312	0.564	-0.512	-0.418	0.452	-0.15	-0.138	-0.155	-0.104	-0.068	0.889							
RELEV	0.703	-0.218	0.54	-0.267	-0.309	-0.285	0.246	0.136	-0.017	0.479	0.467	-0.432	-0.126	-0.125	-0.066	-0.174	-0.155	-0.168	0.825						
SCAR	0.654	-0.159	0.562	-0.295	-0.36	-0.313	0.347	0.041	-0.126	0.504	0.406	-0.438	0.025	0.053	0.062	-0.059	-0.053	-0.244	0.598	0.766					
SIO	-0.277	0.633	-0.282	0.783	0.748	0.686	-0.704	0.325	0.59	-0.524	-0.426	0.422	-0.173	-0.152	-0.163	-0.152	-0.103	0.779	-0.151	-0.283	0.89				
SL	0.589	-0.253	0.628	-0.303	-0.343	-0.278	0.305	0.121	-0.051	0.482	0.441	-0.444	-0.093	-0.125	-0.077	-0.195	-0.166	-0.262	0.551	0.507	-0.257	0.716			
T&A	0.558	-0.579	0.426	-0.691	-0.678	-0.684	0.713	-0.142	-0.53	0.754	0.621	-0.334	0.158	0.106	0.137	0.054	0.026	-0.657	0.412	0.482	-0.679	0.362	0.886		
TEO	0.326	-0.37	0.399	-0.194	-0.248	-0.419	0.489	-0.094	-0.293	0.55	0.658	-0.136	0.099	0.073	0.138	0.066	0.048	-0.202	0.299	0.242	-0.22	0.31	0.393		
TRP	0.479	-0.428	0.499	-0.223	-0.327	-0.439	0.549	-0.038	-0.309	0.626	0.748	-0.248	0.058	0.028	0.103	0.069	0.035	-0.297	0.413	0.451	-0.283	0.474	0.474	0.693	

Notes: supplier information overload (SIO); market information overload (MIO); internal legacy information overload (ILIO); incompatibility (INCOMPA); lack of extended enterprise functionality (LEEF); relevancy (RELEV); timeliness & accuracy (T&A); scarcity (SCAR); accessibility (ACCES); shared language (SL); expanding communication channel (ECC); knowledge acquisition (KA).

Appendix I: Significance and Relevance Test

	Original Sample (O)	2.50%	97.50%	P Values
cm_1 -> CM	0.537	0.252	0.47	0
cm_2 -> CM	0.935	0.793	0.915	0
inflex_1 -> INFLEX	0.813	0.484	0.67	0
inflex_2 -> INFLEX	0.847	0.527	0.706	0
ke_1 -> KE	0.59	0.189	0.46	0.034
ke_2 -> KE	0.823	0.17	0.366	0
ke_3 -> KE	0.958	0.572	0.839	0
ke_4 -> KE	0.592	0.04	0.343	0.007
kg_1 -> KG	0.795	0.05	0.293	0.048
kg_10 -> KG	0.664	0.264	0.429	0.061
kg_11 -> KG	0.607	0.19	0.115	0.057
kg_2 -> KG	0.792	0.199	0.427	0.013
kg_3 -> KG	0.695	0.153	0.466	0.012
kg_4 -> KG	0.74	0.096	0.238	0.079
kg_5 -> KG	0.697	0.079	0.328	0.03
kg_6 -> KG	0.566	0.066	0.391	0.046
kg_7 -> KG	0.562	0.243	0.465	0.021
kg_8 -> KG	0.618	0.19	0.375	0.039
kg_9 -> KG	0.547	0.332	0.539	0.049
ki_1 -> KI	0.798	0.281	0.508	0
ki_2 -> KI	0.751	0.325	0.516	0
ki_3 -> KI	0.636	0.216	0.388	0
ki_4 -> KI	0.481	0.302	0.437	0
ks_1 -> KS	0.746	0.519	0.788	0
ks_2 -> KS	0.577	0.235	0.47	0
ks_3 -> KS	0.621	0.381	0.602	0
leki_1 -> LEKI	0.921	0.422	0.695	0
leki_2 -> LEKI	0.877	0.268	0.469	0
leki_3 -> LEKI	0.55	-0.083	0.207	0.591
leki_4 -> LEKI	0.667	0.137	0.276	0
lfki_1 -> LFKI	0.886	0.304	0.522	0
lfki_2 -> LFKI	0.821	0.187	0.345	0
lfki_3 -> LFKI	0.891	0.366	0.571	0
lfki_4 -> LFKI	0.609	-0.127	0.201	0.776
liki_1 -> LIKI	0.922	0.369	0.614	0
liki_2 -> LIKI	0.821	0.118	0.299	0
liki_3 -> LIKI	0.512	-0.045	0.263	0.265
liki_4 -> LIKI	0.878	0.292	0.501	0
lqdi_1 -> LQDI	0.892	0.287	0.533	0
lqdi_2 -> LQDI	0.794	0.13	0.353	0
lqdi_3 -> LQDI	0.533	-0.088	0.277	0.412
lqdi_4 -> LQDI	0.915	0.307	0.579	0
lqui_1 -> LQUI	0.828	0.249	0.453	0
lqui_2 -> LQUI	0.821	0.296	0.473	0
lqui_3 -> LQUI	0.538	-0.034	0.249	0.153
lqui_4 -> LQUI	0.856	0.29	0.527	0
teo_1 -> TEO	0.639	0.277	0.519	0
teo_2 -> TEO	0.51	0.072	0.316	0.002
teo_3 -> TEO	0.716	0.448	0.827	0
teo_4 -> TEO	0.485	0.24	0.516	0
trp_1 -> TRP	0.549	0.191	0.472	0
trp_2 -> TRP	0.534	0.246	0.438	0
trp_3 -> TRP	0.504	0.141	0.339	0
trp_4 -> TRP	0.547	0.247	0.454	0
trp_5 -> TRP	0.71	0.348	0.602	0

Note: inflexibility (INFLEX); cultural misfits (CM); low quality downstream information (LQDI); low quality upstream information (LQUI); lack of interactional knowledge inventory (LIKI); lack of functional knowledge inventory (LFKI); lack of environmental knowledge inventory (LEKI); trustful environment within organisation (TEO); trustful relationship with business partners (TRP); knowledge selection (KS); knowledge generation (KG); knowledge internalisation (KI); knowledge externalisation (KE)