The influence of online review adoption on supply chain performance: a hybrid simulation study

by

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ABSTRACT

The development of E-commerce leads to the popularity of online review adoption. Customers who purchase online can seek information about products in online reviews posted by others. Although online reviews have become a norm, existing research mainly focuses on their value from a marketing perspective, with fewer studies linking online reviews to supply chain management. As supply chain management is vitally important to E-commerce, this thesis aims to examine the influence of online review adoption on supply chain management.

To meet this aim, the thesis first studied the mechanisms by which online reviews can influence supply chain performance. Based on a systematic literature review, two mechanisms are proposed, namely the 'connecting-tool' mechanism and 'data-source' mechanism, which can explain the influence of online review adoption in supply chain system.

In addition, the realisation of 'connecting-tool' mechanisms is evaluated, comparing how the influence of online review adoption differs between supply chain configurations. Novel hybrid simulation models combining system dynamics and agent-based modelling were built to examine the influence of online review adoption on the performance of uncapacitated and capacitated supply chains, as well as a closed-loop supply chain. Using supply chain profitability as the performance measure, the results indicated adopting online reviews generally leads to higher supply chain profit, but its influence is highly contingent on different contextual factors, such as quality estimation, capacity constraints and unit lost sale penalties.

Finally, methodological issues are discussed, particularly how online reviews can be integrated into supply chain modelling. Currently, only very few studies adopted analytical models to study the influence of online review adoption on supply chain performance. To fill this gap, a framework called OR-SCM was proposed in this thesis to guide future modelling research in this field.

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CHAPTER 1

INTRODUCTION

1.1 Chapter overview

This chapter provides the introduction to this thesis. The research background of the studies in this thesis is presented, articulating the current development of online review usage and supply chain management practices in E-commerce. After that, the research motivation is discussed. Based on the research motivation, three research questions studied in the thesis are raised. Finally, the thesis structure is introduced at the end of this chapter.

1.2 Research Background

The popularity of the Internet, the change of customer purchase behaviours, and the rapid development of information and communication technologies made E-commerce become an indispensable part of people's life. According to the industrial survey by Statista (2020), current E-commerce has the following features. First, the global sales of E-commerce have reached 3.53 trillion US dollars in 2019 and are projected to achieve 6.54 trillion three years later. Second, apart from the huge absolute monetary value, E-commerce now also accounts for a significant share (14%) of the global retailing industry and is estimated to reach 22% in 2023. Third, E-commerce not only gains popularity in developed countries such as USA and UK, but also experiences fast growth in developing countries like China, Thailand, and Vietnam. These statistics show that E-commerce is transforming conventional business practices and leads to new norms for retailing (Nisar and Prabhakar, 2017).

Moreover, the recent Covid-19 pandemic also drives higher E-commerce adoption by customers (Gao et al., 2020). Because of the lockdown restrictions posted by governments, customer offline purchase has largely decreased, and people start to use online ordering and delivery. It has been found that online traffic in the supermarket industry grows more than 35%

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from January to October 2020 (Statista, 2020). To respond to the surge of E-commerce needs, many companies which previously focused on offline transactions start operating online business (Tran, 2020).

The development of E-commerce also witnesses the change of two things, namely the customer feedback practices (Hu et al., 2017) and supply chain management practices (Yu et al., 2016). On the one hand, the feedback for E-commerce is now conveyed through online reviews, allowing much easier bi-directional/multi-directional information exchange compared with offline word-of-mouth (Dellarocas, 2003). Through reviews, customers can evaluate the product quality based on previous feedback, enhancing the information transparency and thus lifting the purchase satisfaction (Filieri, 2016). On the other hand, in E-commerce, more agile and efficient supply chain practices are expected, as compared with the conventional offline business, E-commerce can face higher uncertainty, more customer requirement, and more intense competition (Bayraktar, 2008). The following texts give some examples of online reviews and practices of supply chain management in E-commerce.

1.2.1 Online reviews in E-commerce

While acknowledging that other review sources exist, including paper-based feedback (such as newspaper reviews) or offline word-of-mouth, in the current E-commerce era, online reviews are undoubtedly the most important information source for customers. According to Worldpay (2017), 93% of US consumers use online reviews ahead of purchasing a new product, with over 50% doing so most or all of the time. Brightlocal (2019) found that 82% of customers will check online review information for local businesses. Further, online reviews for many products and services are more accessible than other information sources. Reviews in printed media such as magazines are constrained by space requirements and may focus more on particular products. By contrast, offline word-of-mouth can be only spread in a relatively small group of people and depends upon the purchasing habits of these customers. Online reviews like those provided by Amazon (www.Amazon.com) can expand the scale of information spreading, make the information much more accessible, and reach more customers (Hu et al., 2017).

	Types	Review forms	Applications	Information richness
Conventional online review format	E-commerce platform reviews	Rating score, texts with word limits, rare use of pictures	Amazon, Taobao	Relatively low
	Third-party reviews	Rating score, texts, pictures	TripAdvisor, Trustpilot	Medium
Emerging online review format	Social networking reviews	Texts with word limits, pictures, occasional videos	Facebook, Instagram	Medium
	Video site reviews	Videos	TikTok, YouTube	High
	Live stream reviews	Live videos	Amazon Live, Taobao Live	High

Table 1.1 Different types of online reviews

Table 1.1 lists different types of online reviews and their applications. Based on their features, this thesis ranks them by their information richness which measures the ability of a certain platform to deliver rich information to eliminate interaction ambiguity (Chesney et al., 2017). Conventionally, online reviews may only be limited as a form of reviews in E-commerce platform or in third-party review sites. For example, online reviews can be posted on the E-commerce platform, such as Amazon and Taobao (www.Taobao.com). Customer feedback from online reviews is usually presented in the form of star-rating or texts having word limits, with rare pictures posted. The platform reviews can be unidimensional (e.g. Amazon) where customers give an overall rating to the products/services, or multidimensional (e.g. Taobao) where customers can rate the products from different perspectives (e.g. quality, after-sale service etc.). Apart from the E-commerce platform, third-party online review applications are also a very important source for posting customer feedbacks. The two most popular applications are TripAdvisor (www.tripadvisor.com) and Trustpilot (www.trustpilot.com), where the former focus on the hospitality business while the latter on all types of business. In the third-party platforms, customer ratings as well as textual evaluations are also the most frequently used review forms.

However, compared with the conventional online review formats, the rapid development of new technology (e.g. 5G networks, virtual reality, social media applications etc.) largely enrich the emerging types of online reviews. Social networking platforms such as Facebook (www.facebook.com) and Instagram (www.instagram.com) can also work as online review applications where the users will post rich textual or pictorial reviews to deliver their product evaluations to their friends/subscribers. Further, with the popularity of video sites, such as YouTube (www.youtube.com) and TikTok (www.tiktok.com), many users upload videos for product reviews. For example, when searching the keywords 'iPhone 12 review', thousands of videos of user feedbacks can be found on YouTube. For such kind of reviews, not only the product rating is given, but almost every possible details of the product can be explained, giving prospective customers rich information. Finally, the development of live stream technology in recent five years also enables a new form of online reviews. Leading applications, such as Amazon live (www.amazon.com/live) or Taobao live (taobaolive.taobao.com), allow the live streamers to showroom and review the products as well as to interact with customers instantly, providing information for customers.

Although online reviews bring new feedback practices and give customers rich information, some issues related to online reviews should also be noticed. For example, the online review manipulation and online review fraud can occur. To promote their products/services, companies can strategically post positive reviews by themselves or buy favourable reviews from others (Hu et al., 2011). Also, online reviews may not always accurately reflect product real quality, as customers can commit self-selection bias (Hu et al., 2017; Li and Hitt, 2008) where customer evaluation on products will be influenced by preference, and such bias may mislead prospective customers.

1.2.2 Supply chain management in E-commerce

In the seminal paper by Mentzer et al (2001), supply chain management is defined as '*the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole'*. To obtain the high performance of the whole supply chain, systemic coordination and appropriate tactics need to be realised by multiple activities. In the

supply chain operations reference (SCOR) model by Supply Chain Council (APICS Supply Chain Council, 2017), the supply chain activities are categorised into five generic types: plan, source, make, deliver, and return. Compared with offline businesses, to cope with the more diverse and complicated market, E-commerce companies have higher requirements on these activities (Yu et al., 2016). Table 1.2 summarises the challenges faced specifically by E-commerce companies and their supply chains.

Plan: • Customer demand of E-commerce changes fast and is difficult to predict (Ying and Dayong 2004; Bayraktar et al., 2008).   • The dynamic and small lot-size orders from online customers require good design of ordering and replenishment plans (Zhang et al., 2016).
Source: • Suppliers and E-commerce companies should have higher collaboration (Singh et al., 2018; Wang et al., 2021).   • The suppliers are expected to provide more flexible and customised offers (Singh et al., 2018).   • Low quality sources will be exposed and complained by customers in online reviews (Cai et al.,2018; Kwark et al., 2014).
Make: • E-commerce supply chain is expected to consider customer voice in product development and make products more customer-centred (Pee, 2016).   • Products sold in E-commerce companies need to avoid quality issues, as the online reviews about quality issues posted by customers can be read and shared to prospective customers easily (Singh et al., 2018).
Deliver: • E-commerce companies need fast delivery, as customers are sensitive to the delivery lead time (Wang et al., 2021).   • The delivery of online products of E-commerce companies can incur high operational costs, especially for cross-border E-commerce (Wang et al., 2021).   • E-commerce supply chain can have difficulty dealing with last-mile delivery (Yu et al., 2017).   • The possibility that customers may not be available to receive a delivery adds complexity to the delivery plan (Özarık et al., 2021).   • The complaints about service delivery failure in online reviews can negatively influence the reputation of E-commerce companies (Gu and Ye, 2014).
Return: • E-commerce faces high volume of return (Walsh and Möhring, 2017).   • It is easier for customers to return products than before, and some customers order multiple items online but then return them just for trying (Bernon et al., 2016; Walsh and Möhring, 2017).   • E-commerce is increasingly difficult to design return networks as customers have increasingly various options on product return channel (Bernon et al., 2016).   • The reverse logistics of E-commerce needs high investment on data management and transportation (Lamba et al., 2020).

Table 1.2 Challenges faced by E-commerce supply chains.

Although multiple challenges have been faced by E-commerce supply chains, the supply chain innovation improves the management performance and help respond to the increased market requirement. In recent years, the development of new technologies such as online review system, big data technologies, drones, and blockchain applications profoundly transform the practices of E-commerce supply chain operations, enabling the supply chain to plan, produce and deliver better products/services in a faster time and more precise manner (Dong et al., 2021, in press). The innovative approaches of operations, such as consignment mode and omni-channel retailing also provide new opportunities for online commercial firms (Zhao et al., 2020; Li et al., 2019b). Specifically, the studies of this thesis are associated with the plan (i.e. inventory replenishment under online review influence), source (i.e. capacitated supplier), and return (i.e. closed-loop supply chain) aspects of the supply chain when online reviews are considered.

1.3 Research motivation

This thesis aims to study the influence of online reviews on supply chain performance. The author's interests in this topic originated from his Masters research which examined the value of social media in supply chains. Building on the Masters studies and some early work in the PhD, the focus started to shift towards online reviews, as a quite new but promising field with many under-explored directions. As the author has a background in system dynamics and inventory management, the simulation was identified as the research method.

Although more and more studies have been conducted to address the influence of online reviews on supply chain, the majority only focus on specific activities of supply chain, such as demand forecasting, sales, delivery, or product return. However, there is a dearth of research evaluating the influence from a *systemic* perspective. The systemic perspective, delineated by Kwark et al. (2014), is where the influence of online reviews is evaluated on the overall supply chain system containing all relevant players (i.e. customer, retailer and upstream supplier), rather than one or more specific activities. Based on their analytic results, Kwark et al. (2014) demonstrated that failing to systemically consider the influence of online reviews on the whole supply chain can result in incorrect understanding eventually inappropriate supply chain

decision making. Therefore, they urged studies to investigate online reviews from a systemic level in future study.

However, although six years have passed, only very few papers start to adopt a systemic perspective to examine online review influence, instead of being more activity-based (see literature review in Section 2.3.1 of Chapter 2). However, the performance change in one or several specific supply chain activities does not necessarily explain the change of the overall supply chain performance. This leaves the influence of online reviews on supply chain management unclear or even probably misunderstood. Therefore, the **first** motivation for this research is to find the generic mechanisms which can explain the influence of adopting online reviews on performance of the supply chain from a systemic level. To be more precise, the generic mechanisms here represent a set of causal relationships that can link the adoption of online reviews (the independent variable), the change of the supply chain performance (the dependent variable) and other relevant variables (moderators and mediators).

Second, the generic mechanisms also stimulated interest in examining whether the realisations of these mechanisms vary between different supply chain configurations. The different supply chain configurations in this thesis mean the alternative structures or designs of the supply chain, such as uncapacitated versus capacitated supply chain, or forward versus return (closed-loop) supply chain. The rationale for this motivation is that although there seem to be generic mechanisms that are capable of explaining how online reviews influence the overall supply chain performance, the influence of online reviews can vary depending on other supply chain elements. Online reviews, once adopted, become one element of the system and their influence on system performance is the result of interacting with other elements of the system. One element that the author is especially interested in is supply chain configuration, as usually the change in configuration can lead to performance change in the supply chain (Cannella et al., 2017).

Third, although a few papers (see Table 2.4) start to systemically examine the online review influence on supply chain performance, none of them considers inventory management in their study. Inventory management is one of the most important activities in supply chains and

numerous studies reflect that the performance of inventory management determines the overall performance of the supply chain (Silver et al., 2017; Sterman, 1989; Lee et al., 1997). Inventory management is usually investigated from a systemic perspective where both market and supply sides need to be considered (Dejonckheere et al., 2004; Tang and Naim, 2004), with its practices relevant to plan, sourcing, delivery, making, and return if reverse logistics are considered (Hosoda and Disney, 2018; Hosoda et al., 2015). Previous research mentioned the potential of online review influence on inventory management only from improving demand forecasting accuracy (Hofmann, 2017), but none of the studies explicitly consider inventory management in the supply chain system when examining the influence of online reviews on supply chain performance. Therefore, this thesis is motivated to fill this gap.

Finally, the **fourth** motivation comes from the author's interests in methodological issues of integrating online reviews in supply chain modelling. Through reviewing previous modelling studies on online reviews, the author found that apart from ignoring the inventory management in the studies, a diverse range of modelling approaches are used to integrate online reviews into supply chain modelling. This reflects the complexity of this topic as supply chain can contain various nonlinearities and customers can be full of heterogeneity. In other words, here lacks a generic modelling framework. Therefore, the author is motivated to develop a generic modelling framework to integrate online reviews in supply chain modelling through synthesising previous work and models in this thesis to provide a guide for future modelling studies.

1.4 Research question

Based on the research motivations, this thesis aims to answer the following three research questions. To respond to the first motivation and to find the generic mechanisms explaining the influence of adopting online reviews on the overall supply chain performance, the first research question is formed as follows:

RQ1. What are the mechanisms by which online reviews influence supply chain performance?

To answer **RQ1**, an extensive literature review will be conducted to thoroughly check the influence of online reviews on different supply chain activities. The generic mechanisms will then be proposed by synthesising the previous research.

Second, to respond to the fourth motivation which is the methodological interests, this thesis aims to propose a novel and generic modelling framework to answer the following question:

RQ2. How can online reviews be integrated into supply chain modelling?

To build this framework, the thesis will synthesise the previous literature with the models developed in this thesis. The development of the framework provides the theoretical support for the second and the third motivation.

Based on the framework, to respond to the second motivation and to compare whether the influences of adopting online reviews vary between different supply chain configurations, the third research question is formed as follows:

RQ3. How does the influence of adopting online reviews differ between supply chain configurations?

RQ3 will be studied using hybrid simulation. When studying this question, to respond to the third motivation, the inventory management will also be considered in the model. In other words, the influence of adopting online reviews on supply chain performance examined in this thesis also includes their influence on inventory management.

1.5 Literature comparison and a brief summary of thesis contribution

By answering the three research questions, the author believes this thesis contributes to previous literature. Although the academic and practical contributions will be discussed in detail in Chapter 7, here the author would like to briefly compare this thesis with previous literature and highlight its contribution in Table 1.3. Considering this thesis both builds theoretic framework (in Chapter 2) as well as conducts mathematical modelling work (in Chapters 3 to 6), the author groups relevant published studies into four groups, and compared those studies with the thesis to indicate its contribution. As online reviews are frequently

adopted in the business-to-customer (B2C) transactions, the author shall clarify this thesis primarily focuses on the B2C perspective. Therefore, the answers to the three **RQ**s as well as the contributions and insights generated from thesis studies are most applicable to B2C supply chains.

Previous literature	Thesis contribution
Empirical studies of online reviews in the supply chain **Definition:** Research empirically examining the influence of online reviews in the supply chain. **Representative reference:** Cui et al. (2018); Chan et al. (2016); Lau et al. (2018); Singh et al. (2018); Abrahams et al. (2015). (see Section 2.3 for more details) **Their contribution:** Empirically explored and confirmed the influence of online reviews in different supply chain activities (e.g. demand forecasting, product development, delivery). **Limitation:** Although these studies explored and confirmed the influence of online review in one or several specific supply chain activities, they failed to summarise a generic mechanism to explain how online reviews can influence the whole supply chain performance.	Through a systematic literature review approach, this thesis answered **RQ1** and proposed generic mechanisms (Figure 2.4) to explain how online reviews can influence the whole supply chain performance. Such mechanisms develop theoretic foundations for future work on this topic. This responds to the **first** motivation.
Supply chain modelling studies **Definition:** The modelling research focusing on supply chain management without considering online review influence. **Representative reference:** Dejonckheere et al. (2003 & 2004); Tang and Naim (2004); Zhou and Disney (2006); Hosoda et al. (2015); Hosoda and Disney (2018). (see Section 3.4 for more details) **Their contribution:** From a mathematical modelling perspective, these studies investigated how different system design and replenishment policies can influence supply chain performance. **Limitation:** These studies in supply chain modelling ignored the online review influence, so they failed to include and study the heterogeneous behaviours of customers in online reviews in the supply chain model.	By answering **RQ2 & RQ3** and proposing a novel simulation framework, this thesis linked supply chain models to online review studies. Such a framework can enable previous supply chain models to integrate customer heterogeneity (e.g. preference, review posting behaviours, product return behaviours, etc.) from an online review perspective. This responds to **the second and the fourth** motivation.
Online review modelling studies	By answering **RQ2 & RQ3** and proposing a novel simulation framework, this

Definition: The modelling research focusing on online reviews from marketing perspective without considering supply chain operations. **Representative reference:** Li and Hitt (2008 & 2010); Hu et al. (2017); Jiang and Guo (2015); Kuksov and Xie (2010); Papanastasiou and Savva (2017). (see Section 3.4 for more details) **Their contribution:** From a mathematical modelling perspective, these studies clarify how online reviews and customer heterogeneity in online review rating can influence retailing activities (e.g. pricing, online review adoption, competition, etc.) and retailer performance. **Limitation:** This group of research only considered online review influence in retailing without considering supply side operations, so the conclusion and managerial insights they draw can be suboptimal.	thesis linked online reviews to previous supply chain modelling studies, enabling a systemic evaluation of online review influence. The simulation methods developed can enable flexible explorations of the influence of online reviews in different supply chain configurations, and capture supply chain nonlinearities (e.g. capacity constraint, customer loss, nonnegative order, etc.). This responds to **the second to the fourth** motivation.
Online-review-supply-chain modelling studies **Definition:** The modelling research considering online review influence on supply chain performance. **Representative reference:** Liu et al. (2018); Sahoo et al. (2018); Minnema et al. (2016); Kwark et al (2014); Cai et al. (2018) (see Section 2.5 for a detailed summary) **Their contribution:** The studies in this group managed to evaluate online review influence on supply chain performance. The more systemic management insights were drawn, and more importantly, they found that adopting online reviews may not always be beneficial for every player in the supply chains. **Limitation:** These studies evaluated the online review influence from an economic perspective without considering the inventory management practice in their models. As inventory management and control policy are highly important in supply chain management, failing to consider them can hinder the way to fully understand the influence of online reviews.	The models proposed in this thesis answered **RQ2 & RQ3** and integrate inventory management in online-review-supply-chain modelling studies. Also, this thesis considered the influences of online review adoption on the performance of the capacitated supply chain and the closed-loop supply chain which are important but ignored by previous research. The management insights derived from the simulation experiments endorsed the value of the thesis. This responds to **the second to the fourth** motivation.

Table 1.3 Literature comparison and thesis contribution

1.6 Thesis structure

This section presents the structure of the thesis. In total, there are seven chapters. The sequence of chapters together with research questions addressed is visualised in Figure 1.1. Apart from the first chapter which is the introduction, the others are briefly introduced below.
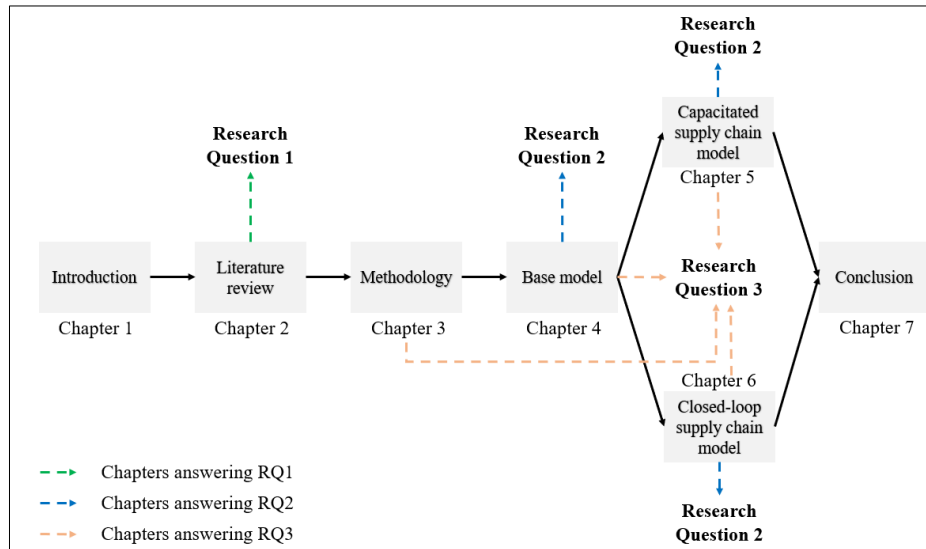
Figure 1.1 Thesis structure

Chapter 2 Literature Review summarises the relevant literature of online review research in supply chain management. Through a systematic literature review, this chapter presents the state-of-art in this field. Papers are first categorised from two broad perspectives, namely topic perspective and research method perspective. After that, considering the nature of this thesis is a mathematical modelling paper, all sampled modelling studies are reviewed in-depth. In Chapter 2, the **RQ1** is answered based on the literature review results and two mechanisms namely 'connecting-tool' mechanism and 'data-source' mechanisms are proposed to explain how online reviews can influence supply chain performance. This chapter is built based on the following publication:

Huang, S., Potter, A. and Eyers, D., 2020. Social media in operations and supply chain management: State-of-the-Art and research directions. International Journal of Production Research, 58(6), pp.1893-1925.

Chapter 3 Methodology presents the methodology for the whole thesis, with a focus on modelling and simulation. The research paradigm and philosophical stance are discussed,

followed by the specific techniques used. Two main techniques, system dynamics and agent-based modelling, are introduced in detail. Finally, the generic simulation processes are listed, working as a guideline for the following chapters. Chapter 3 starts to develop the answer to the **RQ2**.

Chapter 4 Base model develops the base model for the thesis, where an uncapacitated forward supply chain is proposed. Hybrid simulation based on system dynamics and agent-based modelling is conducted to examine the online review adoption influence on supply chain profitability. Analysis of variance (ANOVA) is applied to analyse the results. Apart from online review adoption, two other independent variables, namely product quality estimation and length of lead time, are considered. Chapter 4 partly addresses **RQ2** and **RQ3**. This chapter is adapted from the publication:

Huang, S., Potter, A. and Eyers, D., 2021. Using simulation to explore the influence of online reviews on supply chain dynamics. *Computers and Industrial Engineering, 151, p.106925.*

Chapter 5 Capacitated supply chain model extends the base model and considers the influence of online review adoption on the capacitated supply chain performance. The simulation experiments consider four variables, including online review adoption, quality estimation, capacity constraint level, lost sale penalty level. Chapter 5 partly answers **RQ2** and **RQ3**. This chapter is based on the publication:

Huang, S., Potter, A., Eyers, D. and Li, Q.,2021. The influence of online review adoption on the profitability of capacitated supply chain. Omega: the international journal of management science, 105, p.102501.

Chapter 6 Closed-loop supply chain model extends the base model to include product return. Because of adopting online reviews, customer purchase intention and return decision are both changed. To examine the influence of online review adoption on closed-loop supply chain performance under different contexts, independent variables including online review adoption, quality estimation, and unit reverse supply chain cost are considered in the simulation. Chapter 6 partly answers **RQ2** and **RQ3**.

Chapter 7 Conclusion summarises what this thesis has done and the answers to all the research questions. After that, the contributions of this thesis are discussed. Finally, the limitation of the models and relevant future research opportunities are listed.

1.7 Chapter summary

In this chapter, the background and the motivations of the research are introduced. The research questions studied in this thesis as well as the thesis structures are discussed and listed. From the following chapter, the research questions will be studied and answered.

CHAPTER 2

LITERATURE REVIEW

2.1 Chapter overview

This chapter reviews the previous literature relevant to the online reviews in supply chain management. To provide a comprehensive appraisal of the research landscape, a systematic literature search is conducted. The studies on the influence of online reviews from supply chain management perspectives are collected and analysed. Specifically, this chapter first categorises the supply chain activities that can be influenced by online reviews and the functions of online reviews in these activities. After that, the generic mechanism of how online reviews can influence supply chain performance is discussed. Apart from the summary of the topics investigated in the previous literature, the research methods adopted by the sampled studies are also summarised. Finally, because of the quantitative nature (mathematical modelling) of this thesis, all mathematical modelling studies collected are analysed in detail.

2.2 Literature collection

To achieve a thorough literature collection and appraisal, the literature review in this thesis follows a systematic manner. The studies examining the influence of online reviews on supply chain management is systematically searched and collected from academic databases. To supplement literature sampling, the studies about the influence of social media on supply chain management which are systematically reviewed in Huang et al. (2020) are also considered. Essentially, in many studies, even in top journals, researchers tend to include online reviews as a type of social media (e.g. Chan et al., 2016; Gu and Ye, 2014). The framework for categorising the literature is based on that developed in Huang et al. (2020) and is outlined in more detail in Section 2.3.

To ensure the rigour of conducting the systematic literature review, the procedures suggested by Denyer and Tranfield (2009) are followed. Figure 2.1 outlines the literature sampling processes. The author performed a systematic literature search in three commonly used databases (i.e. Scopus, EBSCO, ProQuest) with the search strings in Table 2.1 focusing on online reviews and supply chain. The search scope is within the title/abstracts/keywords of refereed English academic articles available up to the end of 2020 including those in press. This process yields 531 articles (Scopus: 329, EBSCO: 26, ProQuest: 176).

Online review related strings	+	Supply chain related strings
'customer review' OR 'product review' OR 'online review'		'supply chain' OR logistics OR operations OR transport*

Table 2.1 Search strings for online reviews in the supply chain

After removing duplicates among the three databases, there are 436 papers. Then, each paper is filtered by its title, abstract or the whole text when necessary, and 76 papers are sampled. These papers are then supplemented by papers from Huang et al. (2020). Considering some of the studies in Huang et al. (2020) are irrelevant to online reviews, only those focusing on online review influence on supply chain management are sampled. This results in 115 papers collected. Finally, five papers are added to the literature list by checking the reference of sampled papers and search engine recommendation. The whole process yields 120 papers.
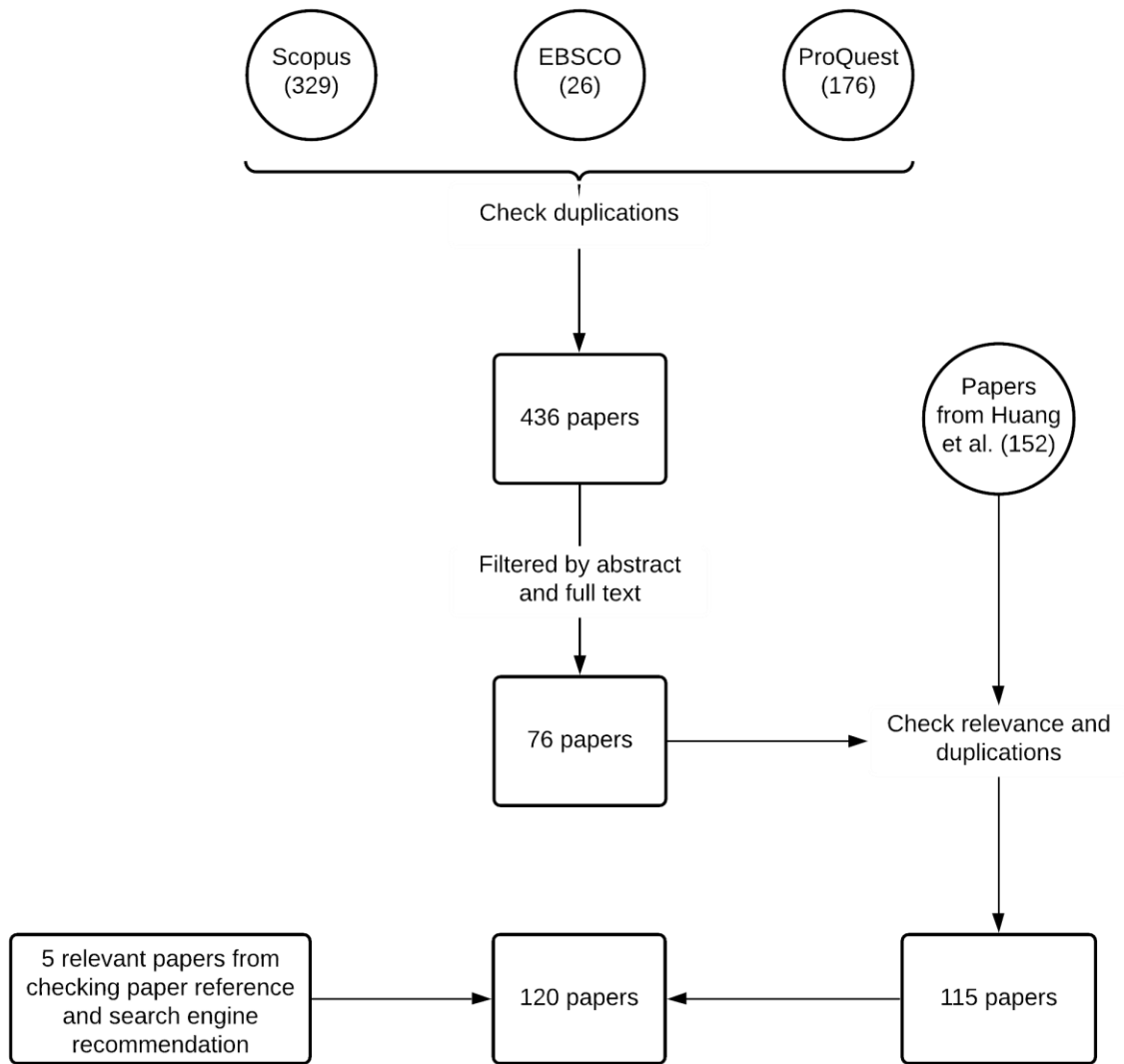
Figure 2.1 Paper sampling process

By counting the number of sampled papers in each year in Figure 2.2, it can be identified that the first article was found in 2009, with steady growth commencing after five years. The number of publications shows this area starts attracting focus from the academic community, but it is still in its infancy and needs more investigations.
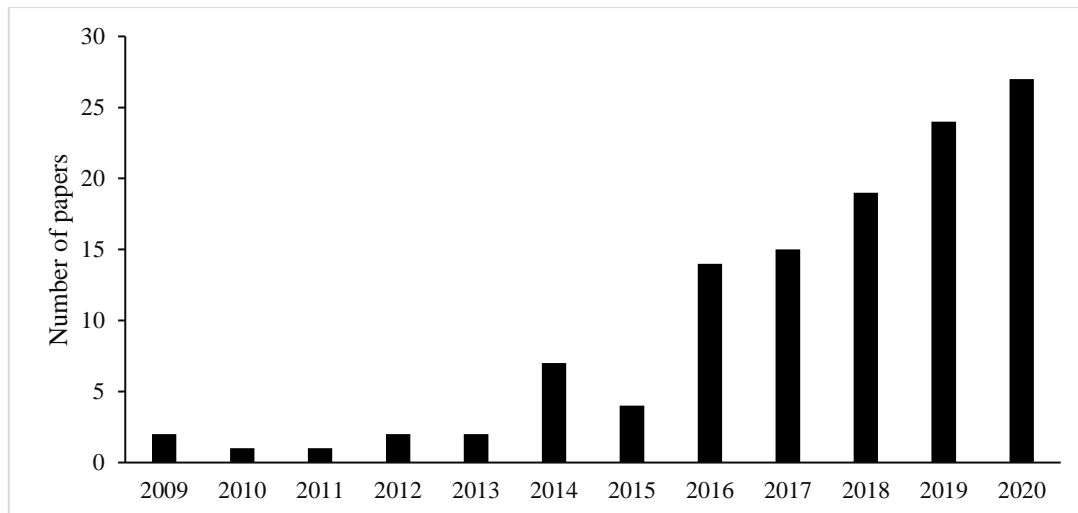
Figure 2.2 Number of papers by year

2.3 Results of research topics

To summarise the topics in the collected literature, the papers were coded from two perspectives, namely the supply chain operations perspective and the online review information sharing perspective. The former aims to summarise what kind of activities in the supply chain (e.g. sourcing, return etc.) can be influenced by online reviews, while the latter categorises the functions of online reviews enabling information sharing between different players in the supply chain.

To code papers from the supply chain operations perspective, the coding scheme was initially developed based on Supply Chain Operations Reference (SCOR) model (APICS Supply Chain Council, 2017), as it is widely used as a standard of practices of supply chain management by practitioners and researchers (Akkawuttiwanich and Yenradee, 2018), and the performance of supply chain in multiple industries have been improved through properly applying SCOR model (Ntabe et al., 2015). Based on the SCOR model, five generic supply chain activities, namely 'planning', 'sourcing', 'making', 'delivery' and 'return', were initially selected to form the coding scheme. However, the author found there are papers focusing on product development, but product development is not the topic addressed explicitly in the SCOR model. As previous literature on supply chain and operations management indicated that product development is also important activities in supply chain management (Mentzer et al., 2001;

Cooper et al., 1997), the coding scheme was extended to include topics related to online reviews in product development and product manufacturing, and changed the 'making' code to 'product development and production'. Moreover, the SCOR model focuses on the physical supply chain, but substantive selected papers were found related to service supply chains, such as bank services, insurance, or public transportation (e.g. airlines). Therefore, the scope of 'product development and production' code is extended to include service development, consistent with the framework of service supply chain management (Ellram et al., 2004; Baltacioglu et al., 2007; Giannakis et al., 2018). Also, it was found that under the 'planning' activities, the studies mainly focus on demand planning. More precisely, the collected papers related to 'planning' focus on how online reviews can influence supply chain demand and how companies can make their plan under such influence, such as adjusting their forecasting methods. Thus, the author changed 'planning' to 'demand management' to fit the topics in the collected paper, and this code includes the papers discussing how online reviews can influence supply chain demand, and how companies can develop methods based on online review information for future demand forecasting. This is also similar to the coding practices in previous operations and supply chain systematic literature reviews (e.g. Nguyen et al., 2018; Choi et al., 2018).

Turning to the perspective of online review information sharing, the codes were first developed based on previous literature for organisational information exchange in the supply chain. Specifically, the existing literature indicates that companies share and exchange information with different internal and external parties in the supply chain (Thomé et al., 2014; Coyle et al., 2016). Internally, information flows among different functional departments, while externally, information flows between the focal company and their supply chain partners (e.g. upstream suppliers), or between focal companies and the public or the end customers (Singh and Power, 2014; Mentzer et al., 2001). Although there is no sampled paper reporting departmental information sharing and exchange based on online reviews, other two ways of information sharing exist, including information sharing (1) between companies as well as (2) between company and end customers. Apart from these two types of information sharing, the author also added another code called customer-customer information sharing, as this is the original purpose of using online reviews for product evaluation. Therefore, the three types of information sharing are enabled by online reviews, which are coded as online review functions. The detailed definitions of the three functions are provided in Section 2.3.2

2.3.1 Different supply chain activities that can be influenced by online review adoption

Based on the coding scheme, the papers were categorised into five generic supply chain activities that can be influenced by online reviews, with some papers coded more than once as multiple activities are studied in the same research. The definitions of activities and their related themes are presented in Table 2.2. The table shows that the most frequently studied activity is product development and production. This is understandable as online reviews by their nature are used to provide feedbacks on products, and the negative feedback or customer suggestions can be used to support new product development. On the contrary, sourcing and return and reverse logistics are the least studied activities, indicating the research gaps. In the following text, each activity is introduced in detail.

Themes	Number of papers
Activity: Product development and production	**79**
Scope: Topics related to the influence of online review on product/service design, development, and production process improvement	
Topics:	
1. Physical product development and production process improvement under the influence of online reviews	31
2. Service product development and improvement under the influence of online reviews	50
Activity: Demand management	**38**
Scope: Topics related to online review influence on demand generation and forecasting	
Topics:	
1. Demand forecast accuracy improvement based on online review information	26
2. Demand generation influenced by online reviews	12
Activity: Delivery	**11**
Scope: Topics related to online review influence on product delivery and logistics	
Topics	
1. Logistics process improvement and optimisation	8
2. Online review as a channel for management response	3
Activity: Sourcing	**6**
Scope: Topics related to online review influence on sourcing and supplier management	
Topics	
1. Supplier pricing considering online review influence	5
2. Supplier selection based on online review information	1
Activity: Return and reverse logistics	**4**

Scope: Topics related to online review influence on product return and reverse logistics process

Topics

1. Online review as an information source to support return rate analysis	3
2. Return policy making under online review influence	1

Table 2.2 Number of papers coded by different supply chain activities

2.3.1.1Product development and production

Companies that develop and produce appropriate products which fulfil customer needs can gain higher customer satisfaction (Zhang et al., 2019). Appropriate product development and production are achieved through accurate identification of customer requirements (Jin et al., 2016; Petersen et al., 2005). The sampled literature indicated that online reviews are valuable for product development and production. The information conveyed in online reviews from customers can stimulate product development ideas (Sigala, 2014) and support production process innovation and redesign (Chan et al., 2016). Through the leverage of the 'wisdom of the crowd', companies can produce and provide more customer-centred products (Singh et al., 2018).

In the sampled papers, online reviews can influence both the development and improvement of both physical and service products. For physical product, there are 31 relevant papers with two focuses, namely product development idea elicitation and production process improvement. The product development idea elicitation is the more popular topic with 25 papers, and the influence of online reviews on this topic has been observed in multiple industries. For example, in the consumer electronic industry, through analysing the online reviews posted by customers, the product features leading to customer satisfaction and dissatisfaction can be captured for smart phone and camera (Kangale et al., 2016; Malaquias and Silva, 2020; Wang et al., 2018). The product features that lead to positive customer experience can then be applied to new products to optimise product design (Lai et al., 2018; Chan et al., 2016 & 2017). Also, the information conveyed in online reviews was found useful for informing product development in the food industry (Mathayomchan and Taecharungroj, 2020; Mishra et al., 2017) as well as the fashion industry (Maiyar et al. 2019) where the ideas elicited from analysing online reviews contributed to the customer-centred product design.

In addition to the topic related to eliciting product development ideas, six papers studied the opportunities for production process improvement from online reviews. In Sigala (2014), the author examined the customer requirement on production sustainability from online reviews and identified the opportunities to make the production process sustainable. In Mishra et al. (2018) as well as Singh et al. (2018), the authors examined the customer evaluations on beef product from online reviews, and they found the ways to change the production and packaging processes to improve the product quality. In the pharmaceutical industry, Ebrahimi et al. (2016) analysed the online review information to identify the side effects of drugs. Using machine learning techniques, the authors built a detection algorithm to automatically process and screen the side effects of drugs from customer online feedback, informing the prescription practices as well as pharmaceutical production. Through applying text mining techniques to the negative online reviews in an automotive forum, Abrahams et al. (2012 & 2015) identified the product defects for automotive as well as the possible improvement opportunities for manufacturing, which can contribute to the reduction in the probability of product recall.

Apart from physical products, the influence of online reviews on service development and improvement is also prevalent. There are 50 studies about service development and improvement with multiple industries reported. Among them, 22 of the papers fall into the tourism and hospitality industry. Through analysing the tourists' online reviews, the service attributes which can lead to positive or negative travelling experience of customers such as location, food service, tour guide, etc. were identified, informing the service improvement opportunities for managers (e.g. Khorsand et al., 2020; Brochado et al., 2020, Chang et al., 2020). Apart from the tourism and hospitality industry, 11 papers are focusing on the public transportation industry, including aviation, rail, boat, and other transportation modes. The customer online feedback on transportation was investigated, and the service improvement opportunities which can contribute to the high service quality were identified (e.g. Bogicevic et al., 2017; Gao et al., 2016). In the sampled papers, other industries were also mentioned that their service development can be influence by online review information, including the health care industry (Hao et al., 2017; Ko et al., 2019; Black et al., 2009) and the house rental industry (Guo et al., 2019).

2.3.1.2 Demand management

Demand management is an essential part of a company's supply chain, and good demand signal processing can enhance the efficiency of supply chain operations (Lee et al., 1997). To effectively manage the demand of the supply chain, capturing demand information and understanding customer purchase intention are necessary (Chong et al., 2017). As online reviews can facilitate the exchange of rich and timely information (Chan et al., 2016), companies can use online reviews to understand customers, as well as integrate online review information into demand forecasting. In the collected studies, there are two research streams related to demand management. The first stream of studies (26 papers) concerns how to use online review information to improve demand forecasting methods (e.g. See-To and Ngai, 2016). Such papers focus on developing forecasting algorithms integrating online review information as inputs. Another stream of studies (11 papers) investigates how supply chain planning and decisions should be made (e.g. supply chain coordination) under the influence of online reviews on demand (e.g. Li et al., 2019a). For this second stream of research, analytical models are frequently used.

For the first stream of research, the studies identified multiple indicators for future demand forecasting from online review information. Useful indicators found in previous research to improve forecasting accuracy included review valence (i.e. average rating for a product), volume (Chong et al., 2016 & 2017), as well as the sentiment within the online review (Li et al., 2016). Some other indicators, although relatively less used, were also identified as effective indicators for the future demand, including the number of votes on helpfulness, the number of questions answered, picture of reviewers (Hou et al., 2017). Using the identified factors as inputs, forecasting methods were proposed, with the techniques ranging from simple regression (See-To and Ngai, 2016) to complicated machine learning algorithms (e.g. Hou et al., 2017).

For the second stream of studies, it focused on how decisions should be made to respond to the influence of online reviews on demand, and mathematical models were usually used in these studies. Under such influence, papers explored how supply chain should make decisions, such as pricing (Yang et al., in press) or supply chain coordination (Liu et al., 2019). Five papers modelled the influence of online review on demand by changing customer utility on product quality (e.g. Yang et al., in press). In other words, the online reviews changed customer

perceptions measured by customer utility on product and thus influenced their purchase decisions. Other papers considered more complicated influence on demand from online reviews where they can not only change customers utility but also influence market competition (Cai et al., 2018; Kwark et al., 2014). In Section 2.5 more details about the mathematical models are discussed.

2.3.1.3 Delivery

Product delivery is important to the supply chain, and the performance of delivery is closely linked to its overall efficiency (Ben-Daya, Hassini, and Bahroun 2019). Companies have traditionally focused on transportation in the physical delivery of materials, but modern service companies may fulfil customer needs virtually, such as using online reviews to deliver management response (e.g. Gu and Ye, 2014). In the sampled literature, 11 papers studied the influence of online reviews on delivery. Among them, the majority (eight papers) analysed online reviews to inform the improvement and optimisation of the logistics and delivery processes, with 3 papers exploring using online reviews as a channel to deliver service.

For studies analysing online review information to improve delivery processes, the reviews about logistics issues in multiple industries were explored, including the food industry (Singh et al., 2018), pharmaceuticals (Liu et al., 2020), 3C industry (computer, communications, and consumer electronics) and cosmetic (Zhu et al., 2017), and most of these studies applied machine learning and natural language processing to analyse the high volume of the data. For example, Singh et al. (2018) analysed the online reviews related to beef products using support vector machine algorithm and sentiment analysis, through which they found different issues and improvement opportunities in product delivery. Liu et al. (2020) applied a latent Dirichlet allocation modelling to the online reviews on pharmacy and found that logistics is the factor that customers care about most. Through the topic modelling process, they discovered the way to improve the logistics in pharmacy. Only one paper is observed to use qualitative content analysis for this topic (Zhu et al., 2017), and the authors used netnography to analyse 1565 reviews manually and found out the opportunities for logistics optimisation, such as increasing delivery speed.

Apart from using online reviews as a dataset to inform logistics decisions, three papers were found employing online reviews as a channel to deliver service. Such a kind of application is specifically for management response for customer service failure recovery. Kim et al. (2015) and Gu and Ye (2014) investigated the phenomenon that hotel managers respond the negative online reviews in the review system. Through review response, customer complaints can be addressed and compensations for the service failure can be offered through online review communications. Their studies showed that online review response can improve service recovery by providing quick and effective solutions to service problems. Fan and Niu (2016) studied the management response in airline companies and showed that online reviews can be an efficient way to deliver after-sale service such as the ticket refund through communicating with customers in the reviews.

2.3.1.4 Sourcing

Sourcing enables companies to obtain products and services from suppliers, and good sourcing management can contribute to the company's competitiveness in the market (Ben-Daya, Hassini, and Bahroun 2019). Sourcing activities include make/buy decision making, supplier selection, procurement management, etc. (Chopra and Meindl 2016). In the sampled papers, two aspects related to sourcing are examined, namely supplier pricing and supplier selection. For pricing decisions of suppliers, the majority of the papers (five papers) employed a mathematical modelling approach to analyse the pricing strategy for profit maximisation (Li et al., 2019a; Liu et al., 2018; Yang et al., in press; Kwark et al., 2014; Cai et al., 2018) when online reviews are adopted. Most of these papers investigated the strategy from a game-theoretic perspective, which is discussed in detail in Section 2.5. Only one paper adopted empirical online review data to study supplier pricing (Pahwa and Starly, 2020). In their study, machine learning algorithms were applied to B2B online reviews, and the price range of 3D printing service suppliers was determined from analysing the reviews. Apart from supplier pricing, one paper by Banerjee et al. (2020) studied supplier selection using online review information. The author adopted a behavioural experiment approach to examine how online review volume and valence can influence the supplier selection process. They found that both indicators can positively link supplier selection decisions.

2.3.1.5 Product return and reverse logistics

Return and reverse logistics concern the practices enabling the reverse flow of products or materials from their point of-consumption to recapture their value (Chan et al., 2012), and efficient return and reverse logistics practices can increase company profitability (Dowlatshahi, 2010). Additionally, increasing expectations and pressure from governments and the public concerning green and sustainable practices also require companies to improve their return and reverse logistics performance (Srivastava and Srivastava, 2006). In the sampled papers, three of them studied the influence of online reviews from the perspectives of product return and reverse logistics (Walsh and Möhring, 2017; Sahoo et al., 2018; Minnema et al., 2016). They analysed how online review information such as volume, valence, and other features can influence the return rate, with the latter two papers investigating the influential power of biased online ratings on it. Different from them, Sun et al. (2021) examined how companies should choose proper return policy under the adoption of online reviews. Using a duopoly model together with game-theoretic analysis, they found when online reviews are adopted, the company should simultaneously consider their pricing decision and their return policy to achieve maximal profit.

2.3.2 Different online review functions

After summarising supply chain activities influence by online reviews, the papers were also coded from the information sharing perspective to categorise different functions of online reviews in the supply chain. To eliminate the ambiguity, the following discussion in Section 2.3.2 and 2.3.3 uses 'customer' to represent end customers in the market, while 'company' to indicate business organisations, such as retailers or suppliers.

Existing literature indicates that companies have the needs to exchange information with different parties in the supply chain (Thomé et al., 2014; Coyle et al. 2016), where information flows between companies and their partners (e.g. upstream suppliers) or between companies and the end customers to support the supply chain decision making (Singh and Power 2014; Mentzer et al. 2001). The sampled papers on online reviews confirm their functions in supporting information sharing and exchange (1) between companies and customers (Chan et al., 2017) as well as (2) between different companies (Pahwa and Starly, 2020). Therefore, two

functions of online reviews influencing company information sharing are suggested. Also, by the nature of online reviews, the basic and original function of them is to enhance the information sharing among customers and improve information transparency. Therefore, in total, there are three functions of online reviews in supply chains. After synthesising the topics of sampled studies, three functions of online reviews are defined below:

Customer-customer information sharing: online reviews enable customers to share information related to supply chain operations with other customers.

Company-customer information sharing: online reviews enable companies and customers to share information related to supply chain operations with each other.

Company-company information sharing: online reviews enable companies to share information related to supply chain operations with other companies.

Figure 2.3 counts the number of each function in the sampled papers, with some papers coded more than once. In the following text, each function will be discussed in detail and linked to the performance of the supply chain.
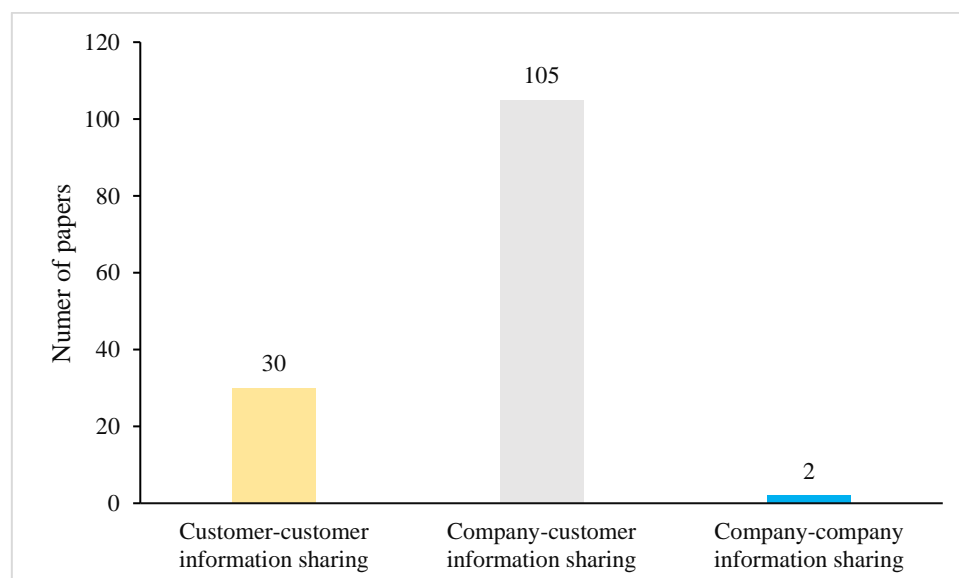
Figure 2.3 Number of papers of different online review functions

2.3.2.1 Customer-customer information sharing

Customer-customer information sharing function enables supply chain information sharing among customers so that different feedbacks on product quality, service provision, logistics

and product return can be conveyed in the posted reviews to influence future customer purchase decisions (Chan et al., 2016; Fan and Niu, 2016). The information can be shared in online reviews in different formats, not only as the review star rating, but also texts, pictures, videos, and expert opinions (Hou et al., 2017; Chong et al., 2016). Through online reviews, prospective customers can gain more information from previous customers, learning more knowledge which is inaccessible through the offline channel (Hu et al., 2017). The online reviews enhance the communication efficiency and effectiveness so that customers can get timely information. Sometimes, such information sharing enhances the information transparency level of transactions. However, it is not always the case as sampled studies also revealed that online review information related to the supply chain can be strategically manipulated by companies (Lee et al., 2018). Under such a scenario, although customers can obtain more information, it can probably mislead their decision-making.

Linking it to supply chain, studies found customer-customer information sharing function does not always contribute to higher performance of supply chains. Instead, the influence of this function on performance is contingent on different contextual parameters, such as product quality, price, operations cost, supply chain power structure etc. (Yang et al., in press; Kwark et al., 2014, Minnema et al., 2016). Therefore, it may suggest that future studies on customer-customer information sharing function of online reviews should not only focus on how this function can influence demand and sales, but also examine this function from a systemic perspective and explore when it will bring positive or negative influence on supply chain performance. This motivates the simulation studies in Chapters 4 to 6.

As suggested in Figure 2.3, although customer-customer information sharing is the original function of online reviews, it is not the most frequently studied topic in the sampled papers. The possible explanation might be the studies for such function are the focus of the marketing research. The sampled papers also present a diverse methodological choice for this function, with 19 studies using quantitative or qualitative empirical methods and the others employing mathematical modelling.

2.3.2.2 Company-customer information sharing

The company-customer information sharing function supports the information flow between companies and customers, enhancing information capture and communication on supply chain related issues. When using online reviews to exchange information with customers or the public, companies both receive and disseminate information. The information sharing can be one-to-one or one-to-many, while the information can flow among different parties. Through online reviews, customers can share information with companies and *vice versa*. For example, airline companies use online reviews to address service problems and to provide possible solutions (Fan and Niu 2016). This is one-to-one/many bi-directional communication between customers and the company, where the company both receives complaints from customers and disseminate solution information. Bhattacharjya, Tripathi, and Ellison (2016) found that when online retailers use online reviews to communicate delivery-related issues with customers, multiple companies including the retailers and the logistics providers can engage in the same piece of online review to inform customers and work on problem-solving processes. This application essentially is many-to-one multi-directional communication, with several different parties involved.

Apart from using online reviews as a communication tool between companies and customers, another theme of papers focused on analysing online review data to inform supply chain decision making. In this case, companies obtain new insights by observing and analysing customer online reviews without directly interacting with customers. The information sharing is thus uni-directional, and opinions and feedbacks about product and service are shared from customers to companies. Research (e.g. Guo et al., 2016; Fan and Niu, 2016) showed when analysing online review information, even simple manual analytical techniques can generate useful insights, such as qualitative content analysis. Also, there are studies proposing more sophisticated approaches like machine learning algorithms and big data methods to capture useful insights such as customer preference on product design (e.g. Jiang et al. 2017; Jin et al. 2016) to support supply chain decisions. Through mining customer shared information, companies can design/re-design supply chain processes (Mishra et al., 2017).

2.3.2.3 Company-company information sharing

Company-company information sharing function enables supply chain information sharing among companies through online reviews. This function is similar to the customer-customer information sharing function, where electronic word-of-mouth of the companies is spread through online reviews. The difference is that the providers of the feedback and electronic word-of-mouth are not the end customers but companies. Two papers studied this function where company-generated reviews were found valuable in evaluating the supplier service quality and informing prospective companies on their supplier choice decisions (Pahwa and Starly, 2020; Banerjee et al., 2020). The lacking of research on this function might provide a future direction where online reviews can be investigated in B2B context. In practice, such type of online reviews provided by downstream companies (i.e. wholesalers or retailers) exists in B2B e-commerce platform, such as Alibaba (www.1688.com). Research on the influence of B2B reviews can probably provide more useful insights for supply and sourcing management for companies compared with insights generated from end customers.

2.3.3 Mechanisms of online review influence in supply chain

To understand the diverse ways by which online reviews influence supply chain performance, the generic mechanisms explaining them are discussed here. To do so, this thesis proposed Figure 2.4 based on the synthesis of results and insights generated from reviewing sampled papers. Figure 2.4 indicates that although online reviews pose impacts on different activities of the supply chain in diverse ways, the mechanisms governing these impacts can be categorised into two generic types: the connecting-tool mechanism and the data-source mechanism. To the best of the author's knowledge, none of the previous studies proposed either mechanism or used either term. This indicates the originality of the mechanisms and the novelty of the proposed framework in Figure 2.4.

Drawing evidence from the sampled papers, Figure 2.4 shows the performance of the supply chain is influenced by improved levels of communication efficiency and effectiveness as well as sensing capability which is defined as 'the ability to spot, interpret, and pursue opportunities in the environment' (Pavlou and El Sawy 2011, p.247). On the one hand, all online review functions can contribute to improving communication efficiency and effectiveness through

connecting-tool mechanism. On the other hand, company-customer and company-company information sharing functions can contribute to improving the sensing capability through the data-source mechanism, with their contribution moderated by supply chain online review analytic capability. In the following context, a detailed explanation on both mechanisms is proposed.
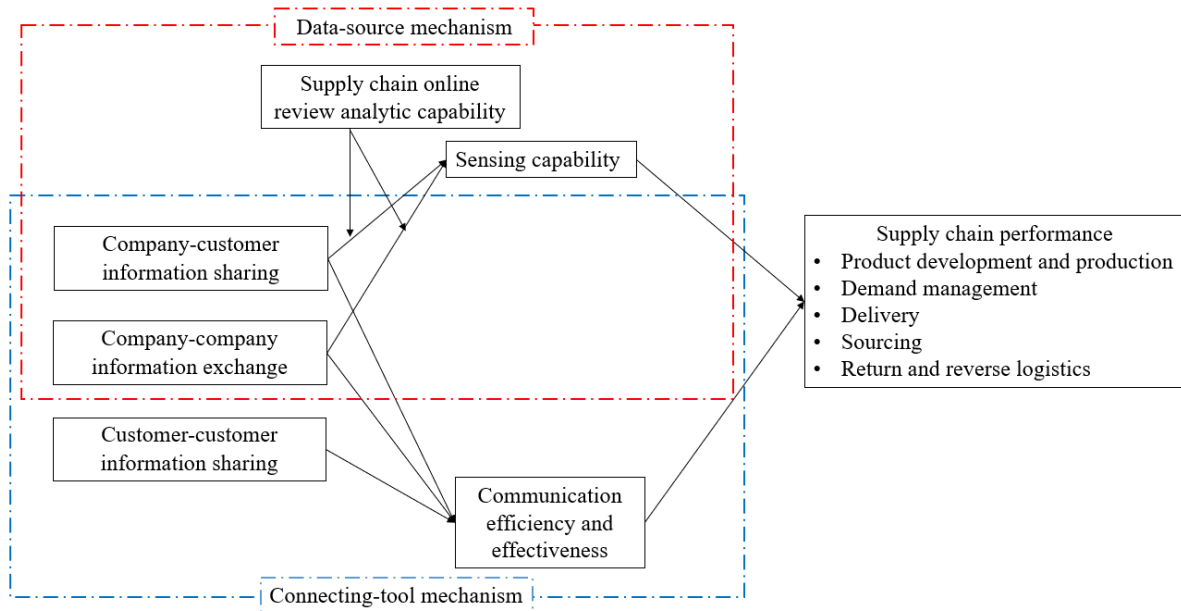
Figure 2.4 Mechanisms of how online reviews can influence supply chain performance

2.3.3.1 Connecting-tool mechanism

The connecting-tool mechanism is defined as: by connecting isolated individuals/organisations, online reviews enable more effective and efficient communications related to supply chain activities between different parties. From a social network perspective, it means online reviews create links between isolated nodes and facilitate the formation of an information-rich network for companies and the whole supply chain (Burt, 2004). The use of online reviews, compared with traditional communication technologies (e.g. email, telephone), makes users (individuals or organisations in this context) more visible and enables them to have more diverse contacts from various parties, which eventually enriches the information in the network (Wu, 2013). The change of supply chain performance is derived from tighter connections among companies and customers across the supply chain by employing three online review functions, and richer and timely information can be shared through such connections (Bhattacharjya, Tripathi, and Ellison 2016; Pahwa and Starly, 2020).

Compared with traditional communication technologies (e.g. email, telephone), the sampled literature showed that connections enabled by online reviews promote two types of interactions of the supply chain. The first type of interaction generates from links between two previously completely unconnected nodes (e.g. a prospective customer and a previous customer), while the second emerges from links between two nodes whose previous connections involve many intermediaries (e.g. an unsatisfactory customer and the staff in the after-sale service department). The former type enhances the network reach, while the latter shortens the network distance, which means richer information can be shared in a timelier manner (Burt, 2009). In addition, information integrity can also be better achieved as a shortened transmission distance reduces the probability of information distortion (Zhang and Venkatesh, 2013).

The sampled literature showed that both types of interactions can be achieved by the online review functions. For example, in the product development process, through the company-customer information sharing function companies can easily reach customers and capture their ideas or complaints about product design in the online review platform (e.g. Sigala 2014, Shih et al., 2014). Such reach can be unrealistic if the traditional communication approach is employed, such as telephone survey, in which only a small sample of customers can be reached and heard. The company-customer information exchange function can also shorten the network distance. For example, when customers have logistics-related issues, customers can make complaints or communicate with logistics providers through online reviews directly rather than contact the retailers first (Bhattacharjya, Tripathi, and Ellison 2016). Compared with traditional approaches, online reviews partly remove the intermediary communication between customers and the companies, thereby shortening the transmission distance.

The customer-customer and company-company information sharing functions can also promote both types of interaction (i.e. expand the network reach and shorten network distance), with more efficiency in enhancing the first type. For example, previous customers can provide feedbacks in online reviews, informing product/service quality to future customers (Kwark et al., 2014). This promotes the connections between different customers which by no means can be connected through traditional tools (e.g. email). Customers can also read online reviews from domain experts (Hou et al., 2017) whose opinions and feedbacks might be inaccessible

or difficult to reach without online reviews (e.g. through magazines). This is also the case for companies. The companies which purchased a supplier's product/service can share their service evaluation of this supplier to prospective companies (Pahwa and Starly, 2020), promoting new links through online reviews.

Under the governance of connecting-tool mechanism, company-customer information sharing function normally poses a positive influence on supply chain performance according to sampled studies. However, it should be noted that the connecting-tool mechanism behind customer-customer and company-company information sharing function can present a more diverse influence on supply chain performance. Undoubtedly, both functions of online reviews can give prospective customers/companies more information about the product, but the influence of such extra information may not always pose a positive stimulus to supply chain performance (Minnema, 2016). The diverse effect is interesting as it determines when online reviews should be adopted/not adopted, and is an area for research within this thesis.

To summarise, as a connecting tool, online reviews enable new and shorter connections, lead to a more efficient and effective communication within supply chain activities, and eventually (positively/negatively) influence supply chain performance.

2.3.3.2 Data-source mechanism

The data-source mechanism is defined as: online reviews work as a data source to support supply chain analytics and enables a higher sensing capability of companies. In this definition, 'data' concerns all accessible online review posts. Sometimes, the data is in large volume and high variety, and it is considered as big data (Hou et al., 2017). The data encompasses not only the reviews sent to companies, but also all other possible relevant posts such as posts in the third-party review platform (e.g. TripAdvisor). Supply chain analytics here refer to apply AI/big data techniques, statistical analysis, or other methods (e.g. qualitative content analysis) to analyse data for supply chain decision making. Unlike when online reviews work as a connecting tool, the emphasis here is that the data volume is relatively large and variety is diverse so that the valuable information and insights need to be extracted by using data analysis techniques rather than through direct communication in online reviews.

Mining and analysing the rich information embedded into online review data enable companies to identify and better understand the market opportunities and threats relevant to operations and supply chain activities (Abrahams et al, 2015), which helps companies configure resources to seize opportunities or tackle threats. In other words, it essentially enhances companies' sensing capability (Song et al., 2015). With high sensing capability, companies can have sustainable competitive advantages (Teece, 2007). Specifically, the sampled papers revealed that the sensing capability can be mainly improved by analysing the data generated from company-customer information sharing (e.g. Jin et al., 2016; Chong et al., 2017), although one paper also showed the potential for analysing data generated from company-company information sharing (Pahwa and Starly, 2020). Companies can receive or capture the user-generated data from online reviews, and use various data analysis techniques combining artificial/business intelligence, such as machine learning (e.g. Abrahams et al. 2015), or manual coding and qualitative content analysis (e.g. Fan and Niu, 2016) to extract valuable information.

Under the data-source mechanism, the sampled papers indicated that different supply chain activities can benefit from the high sensing capability enabled by online reviews. For example, in demand management and forecasting, market trends and fluctuations can be sensed by adding online review analytics into traditional time series forecasting methods (e.g. Chong et al., 2017), leading to better supply chain planning. For product development and production, mining online review data by using big data techniques enhances understanding about the customer preferences or product defects from which companies can sense new opportunities for future product/service design (e.g. Jiang et al., 2017; Abrahams et al., 2012). For sourcing, companies can more effectively evaluate supplier performance by analysing online review data (Pahwa and Starly, 2020). For return and reverse logistics, integrating online review analytics into product return rate forecasting can lead to a more accurate prediction (Minnema et al. 2016), contributing to the reverse logistics performance.

To summarise, online reviews as a data source supports supply chain analytics, enhances sensing capability, and eventually improves supply chain performance.

Although the online review functions can contribute to the supply chain performance improvement through a data-source mechanism, companies can only leverage the value of online reviews if they have a good capability to collect valuable data from them and generate useful insights through appropriate analysis and interpretation. To include this capability into the causal relationship and better explain the data-source mechanism, existing research on business analytics, social media analytics, and big data analytics (Arunachalam, Kumar, and Kawalek 2018; Kamble and Gunasekaran 2019; Gupta, Modgil, and Gunasekaran 2019; He et al. 2015; Wang et al. 2016) was synthesised and the supply chain online review analytic capability was defined as

> *the ability that companies collect, store, and monitor high quality data (e.g. texts, pictures, videos) relevant to supply chain from online reviews, analyse the collected data with appropriate techniques (e.g. AI/big data techniques, qualitative content analysis), and correctly interpret and utilise the analysis results to support supply chain decision making*

Drawing on the evidence from sampled papers, this construct is regarded as a moderator of data-source mechanism, meaning that only companies with high supply chain online review analytic capabilities can leverage the functions of online reviews to enhance their sensing capability. In explanation, the following discussion will follow the definition of this construct and presents the activation of data-source mechanism from three aspects: the quality of data source, the techniques of data analysis, and the interpretation and utilisation of analysis results.

First, collecting and analysing high quality online review data are necessary for the supply chain management. As online reviews can be a source of big data, they are characterised as large volume, high variety and produced and updated at a high velocity (Hofmann 2017). This not only means various information can be captured from online reviews, but also suggests that not all accessible data is necessarily valuable to inform supply chain decision making. Some data can be meaningless, while other data can be incomplete. In addition, online review data can be purposefully manipulated by others (e.g. Lee et al., 2018), and misleading information can be embedded. In these cases, data quality is low, and collected data cannot accurately reflect the market situation. The results generated by analysing low quality data do little help

or could even harm decision making (Hofmann, 2017). Therefore, the prerequisite to leverage data-source mechanism is to capture high quality raw data before conducting analysis.

Further, as online review data is characterised as high data variety, it contains different data forms, such as texts, pictures, videos (Li et al., 2018), and is usually unstructured (Hofmann, 2017). Therefore, traditional data analytical methods (e.g. regression, qualitative content analysis) may not always readily be applied to such data, and novel methods should be built and employed, such as AI/big data analytics and text mining (Lau et al., 2018; Li et al., 2016). For example, for text data natural language processing can be used, while for pictures and videos image processing is helpful (Li et al., 2018). However, to use these new techniques, companies need to be supported by developed infrastructures and human resources (Arunachalam et al., 2018). Moreover, compared with text analysis, the methods to analyse pictures and videos of online reviews look less developed in the supply chain field, as very few sampled papers address picture analysis and no paper addresses video analysis (Hou et al. (2017) is an example to include pictures in analysis). It can be argued that richer information is contained in pictures and videos, as visual materials can convey more contextual information and make companies sense the market trend and situation better. The lack of picture and video analysis can hide the value of online review information. Therefore, appropriate analytical techniques are necessary and the ability of companies to build and use appropriate analytical techniques is essential to leverage data-source mechanism and enhance sensing capability.

Finally, correct interpretation and utilisation of analysis results are important to the improvement of sensing capability. In addition to the traditional operational information source (e.g. point-of-sale data), the insights generated from analysing online review data essentially provide managers with an extra source of information for decision making (Sahoo et al., 2018; Cui et al., 2018, Choi et al., 2018). It is inevitable that when making decisions, managers need to consolidate the new information generated from online reviews to their previous information. However, how to combine the two and adjust decisions accordingly can be problematic, as sometimes the information suggested from online review analytics can conflict with operational information (Hofmann 2017), and incorporation of different information sources into decision making can lead to biased decisions and suboptimality (Wood et al. 2017). In addition, managers have bounded rationality which can directly influence their decision

making (Choi et al., 2018). Therefore, to accurately sense the market opportunities and allocate resources to pursue them, proper interpretation and utilisation of results of online review analytics are important.

To summarise, high supply chain online review analytic capability can leverage the data-source mechanism to enhance sensing capability.

2.4 Results of methodologies

In this section, the methodological choices of the sampled papers are categorised. Six categories are coded and the number of papers in each category is listed in Figure 2.5. The code 'Machine learning' represents papers using machine learning techniques, such as support vector machine or neural network learning, while 'Statistics & Econometric analysis' represents papers applying statistical and econometric methods such as t-test or linear regression. It can be found that there are some overlaps between two codes, as sometimes the machine learning will use statistical methods (e.g. regression). Therefore, to eliminate ambiguity, a paper will be categorised into 'Machine learning' group if there is a *training* process in the study, regardless of what kind of specific techniques adopted. Otherwise, if there are only statistical/econometric methods used without training process, a paper will be categorised into 'Statistics & Econometric analysis' group.
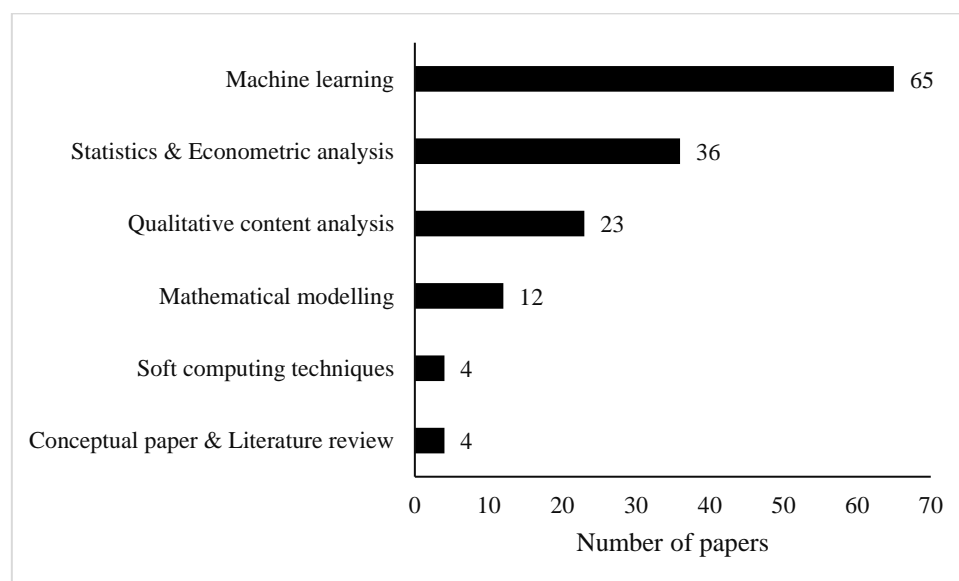
Figure 2.5 Number of papers using different methods

For other groups, 'Qualitative content analysis' represents the papers adopting manual qualitative analysis for online review information while 'Mathematical modelling' represents analytical models or simulation experiments. 'Soft computing techniques' type categorises the papers applying multi-criteria-decision-making techniques or metaheuristics (Chan et al., 2016 & 2017; Mishra et al., 2017; Sathyan et al., 2020), where the soft computing techniques (e.g. AHP, TOPSIS, interpretive structural equation, DEMENTAL) are used in these papers. Finally, 'Conceptual paper & Literature review' categorises the conceptual papers without empirical data or mathematical models.

The analysis of the methodologies of the papers reveals several trends. First, the most widely used method is machine learning as Figure 2.5 shows more than half of the sampled papers apply it to study online review influence in the supply chain. When checking specific techniques of these papers, the most frequently applied technique is natural language processing like sentiment analysis, latent Dirichlet allocation, etc. (Abrahams et al., 2012 & 2015; Hou et al., 2017). This is not surprising, as online reviews are usually a source of big text data, and using machine learning to process text information will be more efficient for handling a large volume of data than manual content analysis (Leeson et al., 2019; Singh et al., 2018; Chong et al., 2016).

Apart from machine learning, statistics/econometric analysis and qualitative content analysis are also frequently used. Compared with machine learning, qualitative content analysis can better handle the complicated questions with imprecise information and generate rich descriptions and contextual insights (Leeson et al., 2019). Therefore, qualitative content analysis is also a good alternative for online review research. In addition, it has been found that ten studies using both methods together (e.g. Brochado et al., 2019; Fan and Niu et al., 2016; Chan et al., 2016 & 2017). In these studies, qualitative content analysis is used to depict the features of online reviews to generate the initial insights while statistics/econometric analysis is conducted to examine them. Although there are studies solely using qualitative content analysis (e.g. Guo et al., 2016), the future trend for empirical online review research would see more mixed method studies.

In addition to the empirical methods, mathematical models are occasionally used in the sampled papers, and the following section will analyse them in detail. The relatively less use of mathematical model suggests this topic is still under-explored from modelling perspective (Kwark et al., 2014). This might reveal the influence of online reviews in supply chain management is yet fully understood, which endorses the novelty and contributions of this thesis. Finally, four papers are found using soft-computing methods, which probably provides an alternative for statistics/econometric analysis.

2.5 Reviews of mathematical modelling papers

As will be noted in section 3.4, this thesis adopts a modelling approach. Therefore, in support of this and to build a case for theoretical contribution, a detailed review of the mathematical modelling papers is now provided.

2.5.1 Topics in modelling papers

After thoroughly reviewing the papers using mathematical modelling/simulation methods, five common topics are identified. It has been found that supply chain pricing and competition attract most research focus, followed by supply chain coordination and product return. Table 2.3 summarised the topics in each paper.

	SC Pricing	SC Competition	SC coordination	Product return	Others
Li et al. (2019a)	✓	✓	✓		
Li et al. (2019b)		✓			
Liu et al. (2018)	✓				
Yang et al. (in press)	✓	✓	✓		
Kwark et al. (2014)	✓	✓			
Cai et al. (2018)	✓	✓			
Minnema et al. (2016)				✓	
Sahoo et al. (2018)				✓	
Guo (2019)	✓	✓			✓
Sun and Xu (2018)					✓
Sun et al. (2021)				✓	
Total	6	6	2	3	2

Table 2.3 Topics in each mathematical modelling paper

2.5.1.1 Supply chain pricing

The topic of supply chain pricing concerns the investigation on the influence of online reviews on the decisions of the wholesaling price (for supplier) and retailing price (for retailer). To study this topic, papers are conducted scenario analysis by comparing the pricing decisions under adopting/not adopting online reviews (Yang et al., in press; Kwark et al., 2014). The collected literature generally shows the supply chain pricing decisions have no unified pattern under the influence of online reviews, and many factors are able to interact with the influence of online review to co-determine the pricing decisions of the wholesaler and the retailer, such as channel structure (Yang et al., in press; Li et al., 2019a), product quality (Kwark et al., 2014; Cai et al., 2018), customer product quality estimation (Yang et al., in press), and supply chain risk level (Liu et al., 2019).

2.5.1.2 Competition

Similar to supply chain pricing, the influence of online reviews on supply chain competition is also studied in most of the papers. Through comparing the scenarios of adopting and not adopting online reviews, the online reviews on competition are found influential on the pricing decisions of competitors (e.g. Kwark et al., 2014; Li et al., 2019b; Yang et al., in press) as well as on the change of competition dominance (Cai et al., 2018, Kwark et al., 2014). Based on various supply chain structure, different types of competitions are examined in these studies. For example, Kwark et al. (2014) examined the competition between two suppliers while Li et al. (2019a), Li et al. (2019b), and Yang et al. (in press) examined the competition between supplier and retailer in multi-channel retailing. One paper by Guo et al. (2019) examined the competition between two retailers sourcing from the same manufacturer. Through extending Kwark et al.'s (2014) model, competitions between more than two suppliers who share the same retailer are examined by Cai et al. (2018) from the online review adoption perspective.

2.5.1.3 Coordination

Coordination here means the comparison between the performance of decentralised and centralised supply chain under the influence of online reviews. This topic is studied using game theory. Based on the number of game players and their power structure, different coordination issues are examined. For example, Yang et al (in press) studied a supply chain whose supplier

sells products through an online channel and an offline retailer, and compared the decentralised and centralised supply chain performance under the influence of online review adoption. Li et al. (2019a) compared the centralised and decentralised supply chain decision making between one supplier and one retailer selling two types of products. The two papers both found that the influence of online reviews on the performance of centralised and decentralised supply chain is contingent on other contextual factors. However, none of them considers in which condition the supply chain can be coordinated successfully, nor do they discuss the contract design under the online review influence.

2.5.1.4 Product return

There are three studies modelling product return and reverse logistics. Minnema et al. (2016) found that higher review valence leads to higher purchase probability but also higher return probability. The numbers of reviews, however, have no significant influence on customer return decisions. They also discussed the influence of falsely positive product rating and illustrated by simulation that if the product rating is over than product's true quality, the sales will increase with higher return probability, which can lead to lower profit. Sahoo et al. (2018) also found that the product rating higher than the true quality can lead to higher return probability, but the authors showed that the volume of reviews has a negative effect on product return probability. Also, Sahoo et al. investigated the features of customers, and found that customers who returned products are more likely to post reviews than those keeping the products. Sun et al. (2021) studied how online review adoption can influence company's return policy selection. They considered two return policies namely no-refund policy and full-money-back policy and compared the total profits between them under the influence of online review adoption. Employing a duopoly model, they conclude that, to maximise the profit, the return policy decisions should be chosen strategically to respond to the influence of online reviews.

2.1.5.5 Other topics

Two papers discussed other topics namely quality management and supply chain system stability. For quality management, Sun and Xu (2018) studied a service supply chain whose product is the collaborative service whose quality level is co-determined by the effort of service providers and customers. Through examining the provision of online reviews and service

outcome information, they compared the effort level for providers and customers under the influence of online reviews. For system stability, Guo (2019) examined the supply chain system consisting of one manufacturer and two competing retailers. Using techniques of control theory, the online review influence on system stability and retail profits is investigated, which gives insights for retailers to better manage customer online reviews.

It can be found that although multiple topics are covered, none of the studies considered capacitated supply chain, closed-loop supply chain or inventory management under the influence of online reviews. As they are all important topics in modelling studies and tightly related to the performance in the E-commerce supply chain, such a gap should be filled, which justifies the originality and contribution of this thesis.

2.5.2 Supply chain model structures

The above modelling studies all include two perspectives in their models, namely customer decision making and supply chain operations, where customer decision making processes are modelled as the consequence of influence from online review information, while supply chain operations are triggered by such consequence. The initial observation of customer side modelling in these studies shows a relatively fixed and unified logic where the online review information changes the customer utility of the product and subsequently affect customer demand. What is more interesting in these papers is the rich variations of supply chain structures. Even though the online review influence on customers is relatively fixed, such influence leads to highly diverse impact on the overall supply chain under different supply chain structure. Therefore, the supply chain structures are summarised here, together with the approaches adopted to integrate online reviews into the supply chain modelling.

After synthesising the modelling approaches, six general structures are summarised in Figure 2.6. Table 2.4 then summarised the model structure in each selected paper, where Li et al. (2019b) discussed and compared two models whose characteristics are close to C and E, respectively.

Notes: 1. **S** means supplier while **R** means retailer. 2. The online reviews are all posted by the end customers
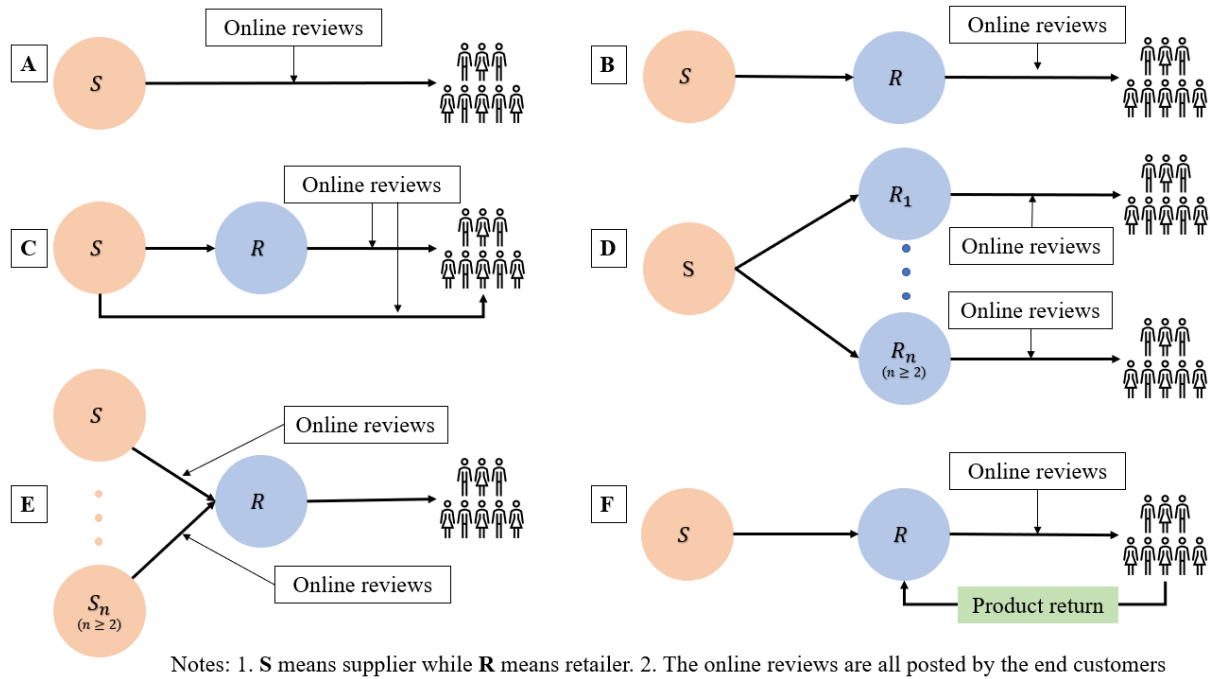
Figure 2.6 Supply chain model structures

	A	B	C	D	E	F
Li et al. (2019a)			✓			
Li et al. (2019b)			✓		✓	
Liu et al. (2019)		✓				
Yang et al. (in press)			✓			
Kwark et al. (2014)					✓	
Cai et al. (2018)					✓	
Minnema et al. (2016)						✓
Sahoo et al. (2018)						✓
Guo (2019)				✓		
Sun and Xu (2018)	✓					
Sun et al. (2021)				✓		✓
Total	**1**	**1**	**3**	**2**	**3**	**3**

Table 2.4 Supply chain structure in each paper

An initial observation of Figure 2.6 tells that the models in the collect research range from very simple forms to highly complex models. For example, structure A and B are the simplest forms which represent a service supply chain and a physical supply chain, respectively. In such structures, only one supplier (structure A) or one supplier and one retailer (structure B) are involved, and the study focus here is how the change of customer demand by online reviews can influence retailer/supplier decision making. As there is only a single type of product, the

information of online reviews reflects the true product quality, and the customer preference (see further chapters for the analytical definition of customer preference) to product is identical.

When it comes to the more complex structures, such as structure C, D, E, competition is introduced as a new factor for online review research in the supply chain. Although the three structures here look similar, their assumptions on different supply and retailing channels lead to the difference of the studies. First, structure C and D are quite alike with each other. For structure C, online reviews can influence the retailer channel as well as the direct-sale channel (of supplier). As the products sold in both channels are sourced from the same supplier, the product quality as well as customer preference is the same for products in both channels, and information reflected from online reviews can be applied to both channels. However, such study assumes customers have different utility on different channels and channel pricing decisions can differ. Under such assumptions, the online review influence varies between channels, leading to asymmetric optimal pricing and operations decisions in different channels. For structure D, it only changes the direct-sale channel to another retailer, which is almost the same as structure C. Although the product is sold in different retailers, the assumptions in structure C are still applicable. The only difference is that, structure D is not limited to two retailers, but can have three or more competing retailers.

For structure E, compared with C and D, customer preference and product substitutability are considered. Specifically, the research (e.g. Kwark et al., 2014; Cai et al., 2018) models a common retailer selling different products sourcing from different and competing suppliers. Different from C and D, the products in the model are 'imperfectly' substitutable. Analytically speaking, this means the customer preference on different products is different but complementary, such as the sum of which is equal to 1 (see Kwark et al. (2014) and Cai et al. (2018) for more details). Such assumption on customer preference is different from that in C and D which assumes the customer preference is the same for different channel products. In structure E, the online review information can apply to reveal product quality as well as influence customer preference, and the studies using this structure examine the influence of online reviews on supply chain decisions and supplier competition dominance.

Finally, models also discuss product return by considering online review influence. The studies having structure F not only focus on how online reviews influence demand in the forward supply chain, but also explore its subsequent influence on product return. However, existing research fails to consider how the influence of online reviews on product return can change the operations of closed-loop supply chain. Therefore, to fill this gap, in Chapter 6 of this thesis, a deeper investigation on how online reviews can influence closed-loop supply chain is conducted based on this structure.

2.5.3 Modelling techniques

Finally, to better reveal the patterns of how models are developed to integrate online review influence into supply chain modelling, the different techniques in collected research are summarised in Table 2.5. It can be recognised that the techniques applied are predominantly static game theory. This is not surprising as such a method is widely used in exploring the behaviours of different parties in the supply chain.

	Game theory (static)	Game theory (dynamic)	Bayesian update	Difference equation simulation
Li et al. (2019a)	✓			
Li et al. (2019b)	✓			
Liu et al. (2019)		✓		
Yang et al. (in press)	✓			
Kwark et al. (2014)	✓			
Cai et al. (2018)	✓			
Minnema et al. (2016)				✓
Sahoo et al. (2018)			✓	
Guo (2019)		✓		
Sun and Xu (2018)	✓			
Sun et al. (2021)	✓			
Total	**6**	**2**	**1**	**1**

Table 2.5 Modelling techniques in collected literature

However, when using the static game theory, the research problem is assumed as static without considering the dynamics of the system. In addition, the assumption on the demand side is simplified to ensure the model is analytically solvable. Such simplifications can be understandable, but when exploring online review influence on supply chains, the studies may fail to fully capture the heterogeneity of the customers and the dynamics of supply chains. This

possible methodological gap of excluding dynamics and heterogeneity can be filled by applying other techniques, such as dynamic game theory or simulation. Therefore, future research should consider dynamic, nonlinear, and heterogenous features of online review influence on supply chain and applied appropriate techniques to complement and cross-check the results found in static game-theoretic research.

2.6 Chapter summary

In this chapter, the relevant studies related to online review influence on the supply chain are systematically reviewed from the perspectives of topic and methodology. The literature review indicates that current research on online reviews in the supply chain mainly focuses on product development and production as well as demand management, and the most frequently explored online review function in the supply chain is company-customer information sharing. The majority of research is found using empirical research methods, with only a few studies employing mathematical modelling techniques. Based on the modelling studies, this chapter also summarised the current landscape of analytical models in studying the influence of online reviews on the supply chain. The results show that current analytical models are relatively simple in model assumptions and methodological choices, suggesting future directions. The gaps identified from the literature reviews are briefly summarised in Table 2.6, highlighting the aspects that are explored in the research questions of the thesis.

	Research gaps	Explored in this thesis
	Supply chain activity perspective	
	1. The influence of online reviews on inventory management	**RQ3**
	2. The influence of online reviews on sourcing activity (e.g. supplier capacity constraints)	**RQ3**
Topic gaps	3. The influence of online reviews on reverse logistics and product return (e.g. closed-loop supply chain)	**RQ3**
	Online review function perspective	
	1. Customer-customer information sharing in supply chain	**RQ1&3**
	2. Company-company information sharing in supply chain	N/A
	System perspective	
	1. Systemic explanations on the influence of online reviews on supply chain performance	**RQ1&3**

Methodological gaps	1. Mathematical modelling (especially simulation)	RQ2
	2. Soft computing techniques	N/A

Table 2.6 Gaps of online review research in supply chain management

Linking back to the research questions of this thesis, this chapter proposed two mechanisms, namely connecting-tool mechanism and data-source mechanism, to explain how online reviews can influence supply chain performance. This contributes to the answer for **RQ1**.

CHAPTER 3

METHODOLOGY

3.1 Chapter overview

This chapter presents the methodological perspective of this thesis. First, the research paradigm of this thesis is discussed, and positivism is recognised as the thesis paradigm. After that, the methodology of the thesis is introduced, followed by the introduction of specific modelling and simulation techniques. Finally, the implementation of the simulation studies in this thesis and their ethical implications are presented.

3.2 Research paradigm and philosophical stance

A research paradigm, according to Kuhn (1970, p.viii), is the 'universally recognised scientific achievements that for a time provide model problems and solutions to a community of practitioners'. It is regarded as 'a view of basic belief…that defines… the nature of the world, the individual's place in it and the range of possible relationships to that world and its parts' (Guba and Lincoln, 1994, p.107). Therefore, a research paradigm directs the choice of research objects (e.g. phenomena and problems) in a discipline, the adoption of the appropriate research strategies and techniques in the research, and the development of explanation for the observed problems and phenomena (Corbetta, 2003; Filstead, 1979).

In social science, multiple paradigms exist. According to Saunders et al. (2016), paradigms can be broadly located into the continuum between objectivism and subjectivism. More specifically, the seminal work by Guba and Lincoln (1994) summarised four main paradigms: positivism, post-positivism, critical theory, and constructivism. Because of the huge influence of Guba and Lincoln's work on the research in social science, this thesis follows their paradigmatic classification as a starting point to introduce the philosophical stance and research design in social science, supply chain management, and finally this thesis. For any paradigm, it

comprises three perspectives, namely ontology epistemology, and methodology (May, 2011). Table 3.1 summarises the information of each paradigm. Consistent with the objectivism-subjectivism continuum into Guba and Lincoln's classification, this thesis does not introduce each of the paradigms individually, but introduces all paradigms together by comparing their diverse ontology, epistemology and methodology. By doing this, different ontological and epistemological stances can be presented in greater detail, and enable a clearer introduction of the paradigm adoption decision of this thesis.

Objectivism			Subjectivism
Positivism	Post-positivism	Critical theory	Constructivism
Ontology Naïve realism: 'real' reality but apprehendable	Critical realism: 'real' reality but only imperfectly and probabilistically apprehendable	Historical realism:'virtual reality' shaped by historical factors; crystallised over time	local and specific constructed realities
Epistemology Dualist/objectivist: findings are true	Modified dualist/objectivist: findings are probably true	Transactional/subjectivist: value-mediated findings	transactional/subjectivist: created findings
Methodology (Reasoning approaches, strategies and methods)			
Reasoning approach Predominantly Deductivism	Abductivism	Inductivism	Inductivism
Research strategy Predominantly Quantitative	Qualitative + Mixed methods	Qualitative	Predominantly Qualitative
Representative research data collection method Structured observation, survey, structured interview, experiments	semi-/non-structured interview, participantory observation, focused group	Ethnography	semi-/non-structured interview, participantory observation, gounded theory, focused group
Representation research analysis method Correlation analysis, regression, econometric techniques	Content analysis, templeate analysis, thematic analysis	Content analysis, template analysis, thematic analysis, discourse analysis	Content analysis, templeate analysis, thematic analysis

Table 3.1 Ontology, epistemology, and methodology for each research paradigm (adapted from Guba and Lincoln (1994), Healy and Perry (2000); May (2011); Lincoln and Guba (2011); Saunders et al. (2016); Eriksson and Kovalainen (2015))

3.2.1 Ontology and Epistemology

Ontology concerns the nature of social reality studied by researchers (Denzin and Lincoln, 2008). The social reality here stands for 'the existence of and relationship between people, society and the world' (Eriksson and Kovalainen, 2015). The views of ontology differ in

researcher perception of how social reality exists. Broadly speaking, the perception can be categorised as objectivism and subjectivism. Objectivism stands for the view that the social reality exists independently of social actors (i.e. people) and their social activities (Sauders et al., 2016). Subjectivism, or sometimes called constructionism (see Bell et al., 2018), stands for the view that social reality is the results of social actors' interaction. In other words, the reality is socially constructed (Corbetta, 2003). More specifically, Guba and Lincoln classified ontology as naïve realism, critical realism, historical realism, and relativism. Table 3.1 synthesises objectivism-subjectivism with four types of ontological views and positions them in a continuum.

Epistemology asks questions about what is knowable, and what constitutes acceptable knowledge (Eriksson and Kovalainen, 2015). The views of epistemology reflect the relationship between researchers and the reality studied (Denzin and Lincoln, 2008). To logically follow different ontological views, the epistemological views of researchers vary, which then leads to the diverse ways they adopt to obtain knowledge (Bryman, 2016).

Consistent with ontology, epistemology can also be broadly categorised into objectivism and subjectivism (Saunders et al., 2016). The epistemological objectivism adopts the assumption of universal and independently existing reality, and thus views the knowledge in social science can be studied and obtained like natural science (May, 2011). In other words, objective epistemology advocates that only those approachable by human senses can be the knowledge, and social reality should be studied based on observable and measurable facts, with aims to obtain law-like generalisations (Bell et al., 2018). Under such a view, because objectivists accept the universal and independent reality, the knowledge must be irrelevant to their own value. This drives them to detach themselves from their own value and conduct value-free research (Healy and Perry, 2000). On the contrary, as the subjectivists view the reality as not universal but socially constructed from social actors and their actions, they epistemologically regard knowledge as the opinions and narratives that form and explain the social reality (Saunders et al., 2016). Such a view drives researchers to study for understanding subjective and distinctive features of social actors rather than for universal laws (Bryman, 2016). Because of the subjective nature, the research conducted by subjectivists is inevitably value-laden and their value is reflected in the studies and the obtained knowledge (Saunders et al., 2016).

In Guba and Lincoln's (1994) paradigm classification, objectivism-subjectivism epistemological views are also adopted, but in a more detailed way. Specifically, they classified them as dualist and objectivist, modified dualist and objectivist, transactional and subjectivist in critical theory, and transactional and subjectivist in constructivism. Each of them is formed under different ontological views and is classified in Table 3.1.

This thesis falls into the research discipline of operations and supply chain management (OSCM). Based on the above descriptions of research paradigms, the paradigms in OSCM are compared in Table 3.2. As OSCM is an interdisciplinary field, the research paradigms are quite diverse and reflect both natural science and social science elements. Essentially, the adoption of research paradigms in OSCM is in the process of evolution. The OSCM research from decades ago was dominated by positivism, and mathematical modelling was the most popular method (Craighead and Meredith, 2008). After that, the research moved to the empirical-oriented, and both quantitative research, such as structural equation modelling (SEM), and qualitative research, such as qualitative case study and field research (Barrett et al., 2011; Ketokivi and Choi, 2014) have been widely conducted, which also enriches the diversity of research paradigms. The following Table 3.2 takes the paradigms from Table 3.1 and provides the relevant studies that adopt each paradigm in OSCM. As it is impossible to list all of them (or even list all representative ones), the author chooses to summarise the features of the relevant research in Table 3.2.

Paradigm	The features of relevant research
Positivism	Majority of the mathematical modelling papers and regression/SEM papers in OSCM fit into this paradigm.
Post-positivism	Such a term is sometimes used interchangeably with critical realism, and Rotaru et al. (2014) summarised relevant studies of OSCM using this paradigm.
Critical theory	Craighead and Meredith (2008) searched previous OSCM studies and concluded that strictly speaking, there was no study fitting into this paradigm. However, based on Headly and Perry (2000), some of the longitudinal ethnographical studies can fit into this paradigm. Therefore, some recent ethnographical studies should be categorised into this paradigm (e.g. Dreyfus et al., 2019)

Constructivism	The majority of the purely qualitative studies in OSCM adopts this paradigm. Also, Chandra and Shang (2017) stated that the studies using methods of open and axial coding should be categorised in this paradigm.

Table 3.2 The relevant OSCM research adopting different paradigms

This doctoral study adopts a largely positivistic approach to the research. The author identifies as holding a positivist philosophical stance, and has confirmed this using the Heightening your Awareness of your Research Philosophy (HARP) chart provided by Saunders et al. (2016, pp.153-155). This means, **ontologically speaking**, the author strongly believes the social phenomenon which should be studied scientifically must work like physical objects that independently exist of researchers' value and interpretation. More precisely, the author identifies with some of the attributes of the **naïve realist** philosophy. In addition, the author's **epistemology** tells that the knowledge, under such a view, should be fully observable, measurable, and generalisable (i.e. law-like generations). Such a view essentially fits the **dualist/objectivist** stance. As a member of Logistics System Dynamics Group (LSDG) at Cardiff University, the author is comfortable with using natural science and engineering methods to study social phenomena. This supports the philosophical stance of the author and the adoption of positivism. Finally, it can be seen from the Table 3.2 that a great amount of research still adopts positivism, which indicates its effectiveness on exploring OSCM topics and endorses the paradigmatic choice of this thesis.

3.2.2 Methodology

Methodology, according to Eriksson and Kovalainen (2015), concerns how research objects can be studied. It includes the choice of strategies in the research design as well as the adoption of specific techniques to implement the design (Corbetta, 2003). As Guba and Lincoln (1994) did not discuss the methodological perspective in-depth, this thesis will first discuss and compare the different reasoning approaches, then introduce qualitative/quantitative strategies and how they fit into different reasoning, and finally outline the specific techniques used in each strategy.

3.2.2.1 Reasoning approaches

Saunders et al. (2016) provide an excellent explanation and comparison between three reasoning approaches in social research in Table 3.3. To better demonstrate each approach, the process flow for research using different reasoning is also provided.

	Deduction	Induction	Abduction
Logic	When the premise is true, the conclusion is true	Known premises are used to generate untested conclusion	Known premises are used to generate testable conclusion which is then tested (on the subsequently collected evidence)
Generalisability	Generalising from the general to the specific	Generalising from the specific to the general	Generalising from the interactions between the specific and the general
Use of data	Data is used to evaluate propositions/hypotheses related to an existing theory	Data is used to identify themes and patterns and build conceptual frameworks	Data is used to identify themes and patterns, locate them in a framework and test the framework through subsequent data collection
Theory	Theory falsification or verification	Theory generation and building	Theory generation or theory modification (for existing theory)
Process flow			

Table 3.3 Explanation and comparison of three reasoning approaches (Adapted from Saunders et al. (2016); Bryman et al. (2016); May (2011))

First, *deduction* is the reasoning approach that the valid inference can be drawn from the true premise (Given, 2008). The true premise here is the already known fact (i.e. existing theory) and the way to perform deduction reasoning is to generalise the already known general fact to a specific case (Reichertz, 2004). In social science, however, the concept of the true premise is extended to the premise that is 'empirically observed' true (Given, 2008). This means, according to Given (2008), the premise can only probably true and the inference drawn from

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the premise should subject to the formal test (e.g. Statistical tests). Such a way of reasoning is commonly seen in the research using regression and SEM where a set of hypotheses for a new phenomenon is drawn from previously published results and then is tested by statistical methods.

Induction, on the contrary, is the reasoning approach that the observations can lead to the development of the theory (Saunders et al., 2016). Different from the deductive approach which aims to generate a certain and valid inference, the inductive approach aims to understand the observation through its inference (Reichertz, 2004). In other words, the established theory and inductive inference are not necessarily true, but only work as a summary of the observed facts which can then be further validated or modified in different contexts (Given, 2008). In social research, such a way of reasoning is normally used to build a new theory for a phenomenon or extend the existing theory to different contexts, and the studies of participatory observation and ethnography usually follow this approach to conduct research.

Finally, the *abduction* approach is the reasoning approach which starts from a 'surprising' phenomenon and draws a 'plausible' (instead of definitely true) explanation for the occurrence of phenomenon (Saunders et al., 2016). This 'surprising' phenomenon is also interpreted by Kovács and Spens (2005) as a 'deviation' of real-life observation. Figure 3.1 presents the Kovacs and Spens' abductive reasoning steps.
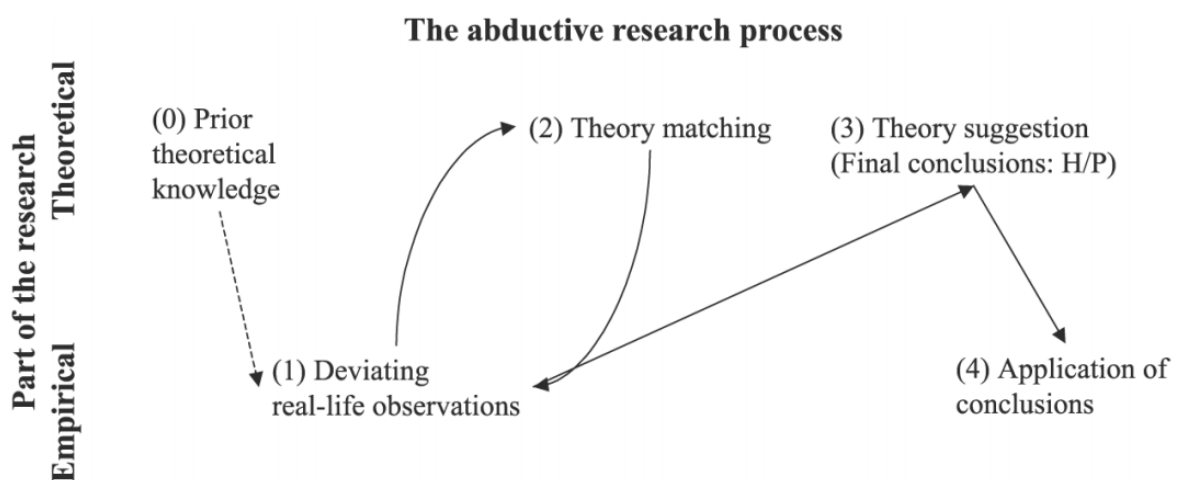
Figure 3.1 Abductive reasoning process (Kovács and Spens, 2005 p.139)

Linking back to the research paradigm, positivism predominantly uses deductive reasoning as it generalises the general to the specific, while critical theory and constructivism normally adopt inductive reasoning as they summarise the specific case to establish the general. Post-positivism, because of its critical realism ontological stance, usually follows an abductive reasoning approach. By adopting a positivistic approach in this doctoral research, deductive reasoning is employed.

Specifically, due to the aim of theoretical verification/falsification in deductive reasoning, the following Chapters 4 to 6 test the existing theory. The '**theory**' here, according to Given (2008), refers to the findings of previously published literature. To be more specific, there is a broad body of existing theory around inventory management and supply chain dynamics (e.g. Lee et al., 1997; Sterman et al., 2000; Silver et al., 2017; Synder and Shen, 2020). Within this, it is well known that changes to demand patterns can have an impact on profitability (Silver et al., 2017; Sterman et al., 2000). Other research on online reviews which is not related to inventory management shows both an impact on buying behaviour (which changes the demand pattern) and profitability. For example, the studies by Li and Hitt (2008 & 2010) documented the influence of online review adoption on customer purchase intention and the profits of companies. Kwark et al.(2014) demonstrated that adopting online reviews can influence the market competition and customer buying behaviour, leading to the change to the supply chain profit. Yang et al. (in press) showed that the adoption of online reviews can differentiate customer choices on selling channels, which brings the impact on the companies' pricing decisions and dual-channel supply chain profits.

Therefore, based on the existing theory from both online review research and inventory and supply chain research, it can be reasonably deduced that adopting online reviews can have an impact on supply chain profitability when inventory management is considered. In the following chapters of the thesis, the author is looking to test whether such impact exists. Specifically, to fill the gaps identified in Table 2.6 of Chapter 2, this thesis not only considers the uncapacitated forward supply chain which is the most widely studied configuration, but also investigates the capacitated supply chain and closed-loop supply chain.

3.2.2.2 Research strategies

After discussing the different reasoning approaches, the research strategies are introduced. There are three strategies in social research, namely quantitative, qualitative, and mixed research strategy, while the last is the combination of the first two. According to Saunders et al. (2016), quantitative research is the studies that collect and analyse numeric data while qualitative research collects and analyses non-numerical data. Although Bryman et al. (2016) argued the distinction between quantitative and qualitative research can be fuzzy, Lawrence (2014) summarised four of the most significant differences between the two strategies. First, they differ in data where quantitative research study 'hard' data (i.e. numbers) while the qualitative studies use 'soft data' (e.g. narratives, pictures, videos). Second, their philosophical positions are different where the ontological and epistemological stance of quantitative strategy is rooted heavily in objectivism (see 'objectivism' in Section 3.2.1) while the qualitative strategy is assumed to adopt subjectivism (see 'subjectivism' in Section 3.2.1). Third, because of the philosophical difference, quantitative strategy normally adopts deductive reasoning to verify or falsify the relationship between independent and dependent variables through performing formal statistical tests, while qualitative strategy often adopts inductive reasoning to understand the complex phenomenon and generate new theories. Finally, the ways to conduct research also differ where quantitative research follows a linear style from research design to data collection and analysis without iteration, while qualitative research is comfortable of conducting iterative research in which the researchers can iteratively modify their research questions even after they finish some parts of the data analysis.

Because of the distinctions between quantitative and qualitative research, they adopt different research methods. For quantitative research, it often collects data through surveys, structured interviews, structured observations, and experiments, while analyses data through correlation analysis, regression, and econometric techniques (Thomas, 2003; Lawrence, 2014). For qualitative research, it often collects data through semi-structured-/unstructured-interview, focus group, ethnography (or netnography for online community by Kozinets (2015)), participatory observation/action research, grounded theory, and experience narratives (Thomas, 2003; Saunders et al., 2016) and analyses data through content analysis, template analysis, or thematic analysis (Lawrence, 2014; King, 2014).

Quantitative and qualitative strategies are not always mutually exclusive, and studies can also combine them and adopt a mix method strategy. The mixed research can take advantage of the strengths of both qualitative and quantitative approaches and, in doing so, may also use an abductive research approach (see studies in Adamides et al. (2012)).

Reflecting the positivist position of the author, and the deductive approach associated with it, the author adopts the quantitative research strategy, specifically mathematical simulations, to study the research questions. The suitability of such a research strategy choice is also endorsed by previous supply chain dynamics and inventory management research in which simulation is widely used (Dejonchkeere et al., 2004; Tang and Naim, 2004). In the following sections, simulation adopted in this thesis is introduced.

3.3 Hybrid simulation in this thesis: a brief introduction

Based on the above discussion about the choice of paradigm and methodology, simulation is identified as the suitable method for this thesis, as a way to overcome difficulty in conducting empirical studies. More specifically, in this thesis, simulation with hybrid methods, including system dynamics and agent-based modelling is used as the methodology to study the research questions. A detailed explanation of why hybrid simulation is adopted is provided below, but in brief, the choice of hybrid simulation rather than single simulation is to better consolidate the customer heterogeneity and supply chain dynamics and nonlinearities in the model.

In the following text, a general introduction to simulation is provided, followed by a brief description of system dynamics and agent-based modelling. The justification of adopting hybrid simulation as the thesis methodology is then given based on research questions as well as its advantages and drawbacks. Finally, the processes of building, analysing, and reporting simulation experiments of this thesis are listed.

3.3.1 Brief introduction on simulation modelling

Simulation, according to Banks et al. (2005), is defined as 'the imitation of the operations of a real-world process or system…[which] involves the generation of an artificial history of a system and the observation of that artificial history to draw inferences concerning the operating characteristics of the real system'. Facilitated by the computer software, simulation is frequently used in operations research to examine the manufacturing, inventory, logistics and transportation systems (Law, 2014).

Based on the different ways of model conceptualisation, simulation models are broadly categorised from three dimensions: stochastic and deterministic; dynamic and static; continuous and discrete (Rossetti, 2015). According to Rossetti (2015), if the system contains randomness in its behaviours, the simulation model is called a stochastic model, otherwise it is a deterministic model. If the system significantly changes with respect to time, the system is a dynamic model, otherwise it can be regarded as static. Finally, if the state change of the system is discrete, the simulation model is categorised as a discrete model, otherwise the model is a continuous model (Law, 2014; Banks et al., 2005). Under this three-dimensional categorisation, in operations research and management science field, four of the most widely used simulations are discrete event simulation (DES), system dynamics (SD) simulation, agent-based modelling (ABM) and Monte-Carlo (MC) simulation (Law, 2014). Figure 3.2 categorised the simulation models, together with the popular methods as well as their software.
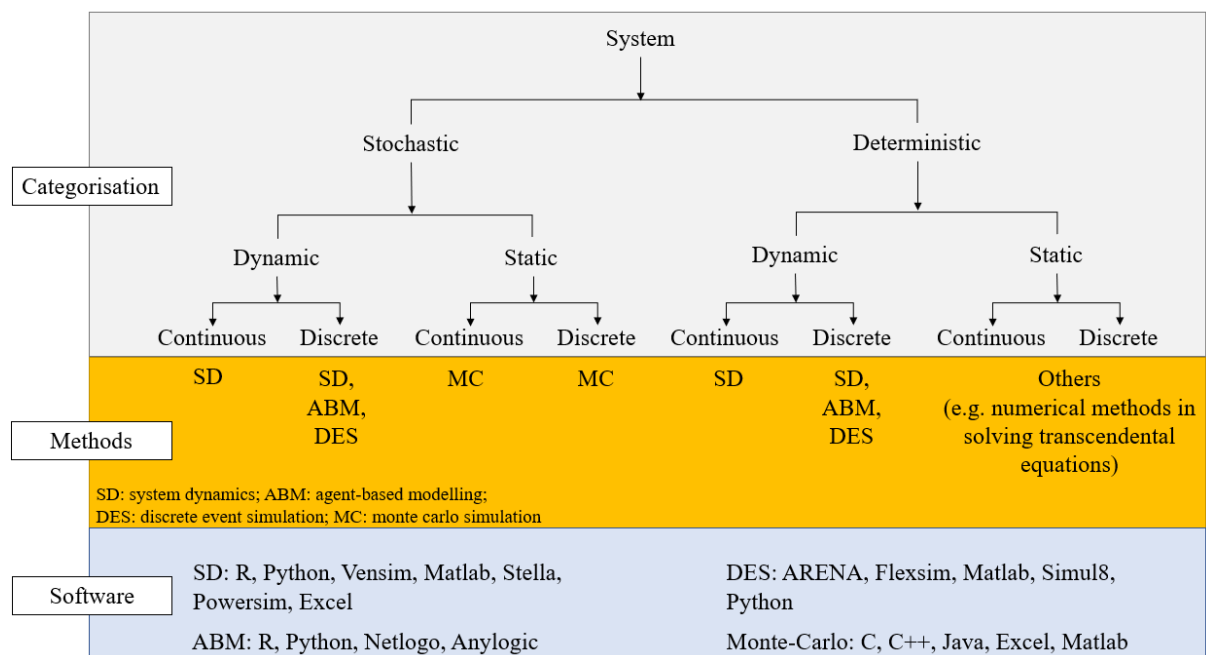
Figure 3.2 Categorisation of simulation models and popular methods and software in each category (partially adapted from Rossetti (2015), Law(2014), Banks (2005), Sterman (2010); Wilensky and Rand (2015))

Compared with other quantitative methods in operations research and management (linear programming, regression etc.), simulation has its own methodological advantages, but also drawbacks. In Table 3.4, both aspects are depicted. The table tells that simulation as a methodology is highly flexible and economical to different problems, especially for those with high structural/dynamic complexity. Also, it has significant strengths in exploratory research. However, the results limited in numerical form probably decrease the explanatory power of simulations.

Advantages	Drawbacks
1. Addressing complexity: Simulations enable explorations in (very) complex models with dynamics and nonlinearity which cannot be depicted by the simple analytical model.	**1.** Simulation Skills: Specific skills and knowledge are needed to learn for building models.
2. Mitigating bounded rationality: Simulations enable understanding of how the	**2.** Unavailable closed-form results: Compared with closed-form analytical results, simulation can only produce

system works instead of how people percept it works.

3. Low cost: Simulation enables investigation on the system without disrupting the real system and with (relatively) low resource required.

4. 'What-if' test: Hypotheses can be tested, and interactions among variables can be explored using simulations.

5. Time compression/expansion: Simulations can either slow down or speed up the time and feedback in the experiments to allow better exploration of how the real system works.

6. Bottleneck analysis: Simulations can enable the discovery of bottlenecks in the process to support further system design and optimisation.

7. Conceputalisation: Simulations are good for conceptualising observations and facilitating concept building.

8. Handling data unavailability: Simulations can handle the situation when parameter data is not available, for example, through sensitivity analysis.

9. Reproducibility: Compared with real-world experiments, simulations can be easily reset and run.

numerical results. Depending upon the simulation approach and software used, it can be unclear how the results emerge from the model structure.

3. Time consuming: The time running simulations with complicated model structure can be long.

4. Interpretation paradox: The interpretation of simulation results can be sometimes difficult, as it can be not easy to distinguish if they are generated from the variable inter-relationship or system stochastic noise.

Table 3.4 The advantages and drawback of simulations (Adapted from Banks et al. (2005), Sterman (2010), Law (2014), Iba (2013) Kelton (2002))

3.3.2 System dynamics, agent-based modelling, and hybrid simulation

In this thesis, SD and ABM are adopted as the methods to develop hybrid simulation models. It will be seen in the following chapters that SD is used to model supply chain while ABM to model online review influence. Therefore, in this section a brief introduction of both is presented, with a specific focus on their applications in supply chain management and online reviews, respectively. Finally, hybrid simulation is introduced to highlight the gap for the research on online reviews in supply chain management.

3.3.2.1 System dynamics

SD, with its roots in control engineering, is a simulation method for complex system analysis from the perspectives of information feedback and delays (Angerhofer and Angelides, 2000). It is founded by Forrester (1961) to analyse the industrial dynamic phenomena, and has been widely used to study different business activities and policies. In the supply chain management field, some early work related to SD is Deziel and Eilon (1967) which proposed a linear production control rule, and Coyle (1977) which studied the management dynamics and developed a production control system model. In Sterman (1989), the well-known "Beer Game" model was published, where SD was applied to explore the decision process of managers and the order variance phenomenon in multi-echelon supply chains. In 1994, John et al. based Auto-Pipeline Inventory and Order Based Production Control System (APIOBPCS) on Sterman (1989) and by extending IOBPCS (Towill, 1982), where the dynamic production processes were depicted by control theory. Later, Dejonckheere et al. (2003 & 2004) applied the system dynamics and control theories to study the bullwhip effect and the influence of information sharing on it.

Figure 3.3 presents the Sterman's model and APIOBPCS. Although represented in different formats, the essence of both is the same. Specifically, to replenish inventory, the order number in each period is equal to the sum of the forecasted demand in the perceived time, (a fraction of) the inventory difference between target and actual inventory on-hand, as well as (a fraction of) the difference between target and actual work-in-process (Disney and Towill, 2003a; Cannella and Ciancimino, 2008).
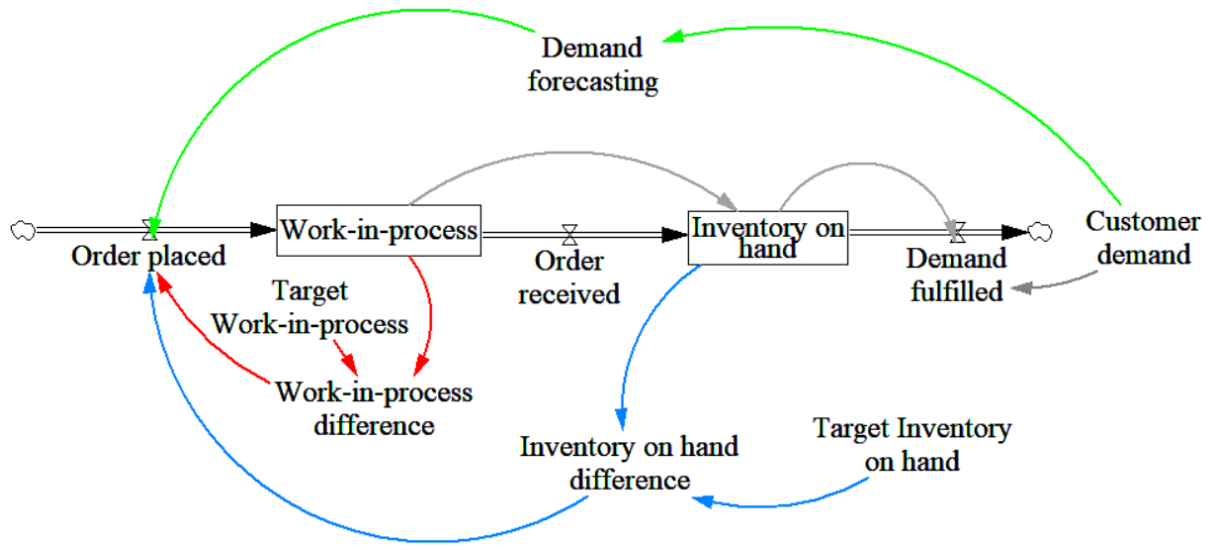
Stock-flow diagram in Sterman's model
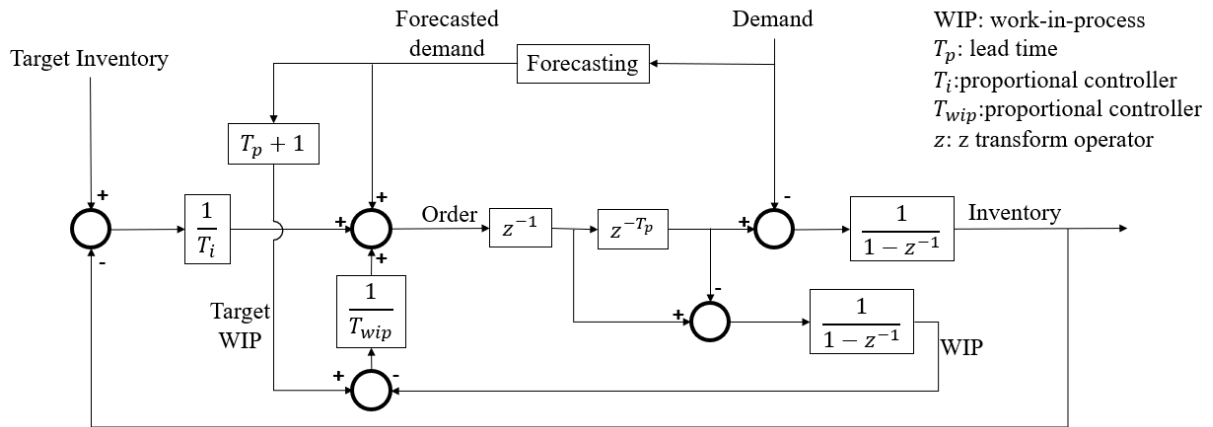
Block diagram of APIOBPCS

Figure 3.3 Beer Game framework and APIOBPCS structure (adapted from Sterman (1989); John et al. (1994); Dejonckheere et al (2003;2004))

Based on this well-developed APIOBPCS system dynamics model, many variations are built to explore various supply chain topics (see Lin et al. (2017) as a detailed summary). For example, Tang and Naim (2004) as well as Zhou and Disney (2006) built the closed-loop supply chain framework to study the dynamics of the supply chain with remanufacturing operations. Potter and Lalwani (2008) simulated the influence of transportation capacity

constraints on supply chain performance. Some representative studies in different topics using APIOBPCS model are listed in Table 3.5.

Authors	Topic
Dejonchkeere et al. (2004)	Multi-echelon supply chain
Tang and Naim (2004)	Closed-loop supply chain
Zhou and Disney (2006)	Closed-loop supply chain
Cannella et al. (2008)	Capacitated supply chain
Potter and Lalwani (2008)	Supply chain and transportation
Disney and Towill (2003b)	Vendor managed inventory
Wang et al. (2012)	Supply chain without return
Spiegler et al. (2012)	Supply chain with nonlinear control
Li et al. (2014)	Supply chain with damped trend forecasting
Boute et al. (2015)	Dual sourcing supply chain
Wikner et al. (2017)	Supply chain decoupling point

Table 3.5 Representative APIOBPCS research

Whilst the current doctoral study does not explicitly consider the dynamic performance of a system (i.e. bullwhip effect or fill rate), the author still argues that the adoption of system dynamics instead of some forms of Monte Carlo simulation is appropriate for the study. This is because, according to Barlas (2020), system dynamics is not only limited itself on focusing on dynamic performance, but 'provide us with strong philosophical grounding and superb tools to model such problems: endogenous principles of systems, causal loop diagrams, stock-flow modelling, and simulation'. As long as the system is characterised by 'feedbacks, accumulation processes, and delays' (Größler et al., 2008), system dynamics is a suitable method to utilise. It shall be seen in the following chapters that the models considered are full of endogeneity and have various feedback loops, different types of delays, and multiple casual relationships. Therefore, although the performance is not evaluated from a dynamic perspective, the author aligns with Größler et al. (2008) and Barlas (2020), and recognises that the use of system dynamics can capture the features of the models and generates valuable insights.

ABM is a simulation method for studying the behaviour of 'agents' as well as their interaction with others and environments (Gilbert, 2019). Although encoding the behaviour of each agent in a simple rule, ABM enables researchers to explore the phenomena in the complex system and processes (Wilensky and Rand, 2015). ABM is widely adopted to study the phenomena in both natural science (Zhang, 2012) and social science (Gilbert, 2019).

In online review research, the application of the ABM method is quite limited. A thorough search in literature yields only 3 papers relevant to this field (Jiang et al., 2020; Bhole and Hanna, 2015 & 2017). Through the observation of previous literature, the author identifies the reason for lacking in ABM in this field is probably due to its academic tradition of analytical reasoning. It can be seen that papers published (Li and Hitt, 2008; Jiang and Guo, 2015; Hu et al., 2017 etc.) tend to derive the analytical results to study the online review influence. However, it can be observed that these papers, although accepted by top journals, all make some compromise. For example, in Li and Hitt (2008), they just calculated the first 20 periods as a demonstration for their analytical results rather than derive the long run results due to the complexity of the online review posting structure. In Jiang and Guo (2015), although fully tractable results are derived, the structure is extraordinarily complicated and is hard to conduct further analysis (e.g. prescriptive analysis) on it. In Hu et al. (2017), their first-order and second-order conditions of the models are not analytically tractable and the authors have to adopt numerical analysis on them. Therefore, although these compromises enable the derivation of analytic results, they also simplify the assumptions on customer heterogeneity in online reviews. In this sense, such an academic tradition of analytical reasoning might probably hinder the way for deeper investigation on the influence of online reviews.

Different from analytical reasoning which focuses on the integrated behaviours, ABM adopts a bottom-up approach (Hamill and Gilbert, 2016), and it will not be hindered by the intractability. However, current ABM studies in this field are quite rare. The paper by Jiang et al. (2020) focuses on online review posting behaviours of customers, without interaction with the market and supply chain. The other two papers by Bhole and Hanna (2015 & 2017) considers the interaction between market sales and online review influence, but they simplified the customer characteristics (e.g. customer preference and sensitivity to the product quality and

price), as well as fail to link it to the supply chain operations. Therefore, the ABM study in online reviews is essentially a gap urgent to be fulfilled, especially in linking online reviews to supply chain study. This endorses the originality and research contribution of this thesis, where a new ABM method is proposed from synthesising previous highly cited analytical work (e.g. Li and Hitt, 2008).

3.3.2.3 Hybrid simulation of SD-ABM

Hybrid simulation is simulation models combining different simulation methods (normally SD, ABM or DES) (Brailsford et al., 2019). Through hybrid simulation, the disadvantages of using a single method can be mitigated and the merits of different methods can be integrated to better capture the features of the system (Tako and Robinson, 2012). In supply chain management, hybrid simulation of SD-ABM gains popularity in recent years. According to Rahmandad and Sterman (2008), SD assumes homogeneity and focuses on system-level behaviour, while ABM can better capture heterogeneity and micro-level behaviour. Therefore, to make use of the advantageous features of both simulation methods to study supply chains, different hybrid models are built.

For example, Barbosa and Azevedo (2018) built a hybrid simulation model to study the engineer-to-order/make-to-order system and evaluate the system performance in different contexts. Ledwoch et al. (2018) combined SD and ABM to study the effect of the network structure of supply chains on supply chain resilience. In their work, SD is used to model the inventory replenishment process while ABM is used to model the supply chain topological structure. Lohmer et al. (2020) studied the resilience and ripple effect of the blockchain-enabled supply chain using SD-ABM in which the authors used SD to model replenishment processes for each agent in the supply chain while ABM for the behaviours of each agent when confronting disruptions. Ponte et al. (2017a) applied SD-ABM simulation to study the inventory policies under different external environments as well as internal supply chain structures and found the supply chain performance is influenced by both external and internal elements. Asif et al. (2016) proposed an SD-ABM simulation framework to examine the performance of circular production system with the market as well as supply complexity considered.

To summarise all simulation studies in 3.4.2.1 to 3.4.2.3, Table 3.6 categorised them based on their research content, which also positions this thesis to show how it fits in previous literature. The table clearly shows that, there is no model integrating online reviews into supply chain modelling using SD and ABM. This demonstrates the novelty of this thesis.

	Agent-based modelling used?	System dynamics used?	Supply chain considered?	Online reviews considered?
Dejonchkeere et al. (2004)		✓	✓	
Tang and Naim (2004)		✓	✓	
Zhou and Disney (2006)		✓	✓	
Cannella et al. (2008)		✓	✓	
Potter and Lalwani (2008)		✓	✓	
Wang et al. (2012)		✓	✓	
Spiegler et al. (2012)		✓	✓	
Li et al. (2014)		✓	✓	
Boute et al. (2015)		✓	✓	
Wikner et al. (2017)		✓	✓	
Jiang et al. (2020)	✓			✓
Bhole and Hanna (2015)	✓			✓
Bhole and Hanna (2017)	✓			✓
Lohmer et al. (2020)	✓	✓	✓	
Ledwoch et al. (2018)	✓	✓	✓	
Asif et al. (2016)	✓	✓	✓	
Barbosa and Azevedo (2018)	✓	✓	✓	
Ponte et al. (2017a)	✓	✓	✓	
This thesis	✓	✓	✓	✓

Table 3.6 Positioning of thesis simulation in previous literature

3.3.3 Justification of adopting hybrid simulation approach

To justify the adoption of hybrid simulation, the author would like to discuss the reasons from three perspectives about (1) why simulation is chosen, (2) why analytical investigation is abandoned, and (3) why hybrid simulation is chosen.

First, the reason for choosing simulation experiments as thesis methodology is guided by the author's positivism research paradigm. As mentioned above, the positivism paradigm leads to

the author's interests in the relationship between online review adoption and supply chain performance. Thus, to study this relationship, quantitative research methods should be adopted. Apart from the guidance of positivism, the adoption of the simulation method is also consistent with previous research tradition in supply chain management (see Table 3.5). Therefore, simulation is suitable for this thesis.

Compared with the simulation, the author also considered the feasibility of analytically deriving the closed-form results of the research question (specifically **RQ3**), but found that to capture the nature of the question, analytical results are not suitable. The nature of the question is nonlinear and full of heterogeneity, making the analytical investigation difficult to apply. For nonlinearity, in E-commerce, customers can leave when products are stock-out. Further, after purchasing, some customers may forget or not be willing to post online reviews. All of these phenomena cause difficulty for analytical derivation. The intractability is also suggested by previous literature. For example, for the model in Chapter 6, previous research has already suggested that it is not analytically traceable (Anderson et al., 2009). As mentioned above, the traditional approach is to ignore these nonlinearities and assume a linear system and derive the analytical results, but in this thesis, linear system assumption may not be representative in the real-world situation, as it leads to the loss of generalisation and explanatory power of the results. Therefore, to embrace the nonlinearity, simulation rather than analytical methods is adopted. Apart from the nonlinearity, customer heterogeneity is another nature of the question and a cause for intractability. Different customers have rich diversification in their pre- and post-purchase behaviours like ordering and returning products, which makes the investigation even more analytically intractable. Therefore, simulation is considered as the suitable method in this thesis.

Because of the nature of the research question, the hybrid simulation becomes a solution, and choosing SD-ABM hybrid simulation approach rather than the single simulation can better capture the features of research questions. First, SD can not only handle the supply chain dynamics, but also nonlinearities such as using the maximum/minimum operators (see formulation in Chapters 4 to 6). Here the choice of SD has largely followed the APIOBPCS frameworks, as this well-developed model can eliminate many validation issues, ensuring the validity and reliability of the research. Also, the rich variations of APIOBPCS framework

enable deeper investigations in the future research. On the other hand, the selection of ABM is largely due to the heterogeneity of the customers. As it shall be seen in the following chapters, to explore and answer the research questions, customer heterogeneity in preference, perceptions and behaviours need to be considered. Compared with SD and DES, ABM is a 'bottom-up' simulation approach (Wilensky and Rand, 2015), enabling the better capture of customer heterogeneity. Therefore, ABM is adopted to model market side activities.

3.3.4 Modelling framework for hybrid simulation

The above discussion justified the suitability of simulation methods. To fully capture the features of how online reviews influence supply chain performance, an appropriate modelling framework should be developed to guide the hybrid simulation. Drawing the lessons from existing research on online reviews and supply chain management (see Table 2.4 and Table 3.6), a hierarchical framework call OR-SCM framework (abbreviation for 'online-review-supply-chain-management) is proposed. Here, only the macro-level of this framework is introduced in Figure 3.4, with the lower-level details developed in the following Chapters 4 to 6. The framework aims to answer the **RQ2**.
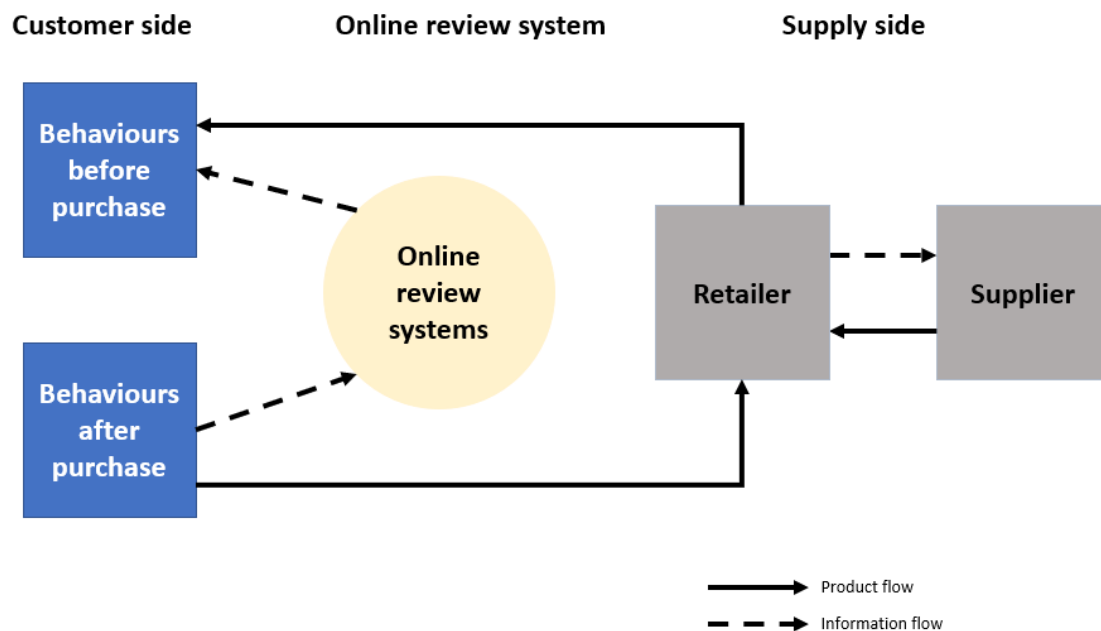
Figure 3.4 OR-SCM modelling framework for hybrid simulation

Through synthesising existing research, Figure 3.4 shows the framework addresses three macro-level perspectives, namely customer perspective, online review system perspective, and supply perspective. First, previous literature suggests that when simulating customer behaviours, two aspects need to be modelled, namely *behaviours before purchase* and *behaviours after purchase* (Kuksov and Xie, 2010; Sahoo et al., 2018; Jiang and Guo, 2015). The pre-purchase behaviours include how customers make their decisions to order products based on their own information and their interpretation of online reviews, while post-purchase behaviours include customer rating process and product return (if the return is allowed) after receiving the product. To simulate both types of behaviours, customer utility is the starting point (with details presented in Chapters 4 to 6). From modelling utility, the model captures the heterogeneity of customers, lending itself to the agent-based modelling.

Second, the *online review system behaviours*, according to existing research, include how system updates and presents product review information (Li and Hitt, 2010; Hu et al., 2017). For the system updating process, studies (Li and Hitt, 2008; Bhole and Hanna, 2017) model it as calculating the mean value of all previously posted ratings. After that, the mean value will be presented in the online review system and used as an estimator for the true product quality (Hu et al., 2017; Li and Hitt, 2008). This thesis adopts this way but notes the existence of other modelling approaches (see Chapters 4 to 6 for a discussion).

Finally, the supply side, according to supply chain literature, includes modelling the *retailer behaviours* and the *behaviours of the upstream supplier*. The behaviours of the retailer primarily concern customer order fulfilment and inventory replenishment (i.e. forecasting demand, placing order, storing products, etc.). The retailer is required to fulfil the orders of end customers by using the on-hand inventory. To replenish this, the retailer needs to place orders to the upstream supplier. The APIOBPCS framework is followed, and the retailer calculates the replenishment value by estimating the future demand as well as considering the on-hand inventory and work-in-process. Once receiving the retailer's order, the supplier will ship or manufacture the products to fulfil the order. Consistent with the practice, the lead time as well as the capacity constraints of supplier will be considered in the following chapters. Also, in Chapter 6, the product return and the reverse supply chain operations are considered, and the returned products will work as a complementary flow of the newly manufactured products to

supply retailer's inventory. In the following section, the introduction of how this thesis implements simulation is presented.

3.4 Methodology implementation: simulation processes

Based on Banks et al. (2005), Rossetti (2015), and Sterman (2010), conducting a simulation project follows generic processes. Following their suggestions, the processes of implementing the simulation studies in this thesis are outlined in Figure 3.5:
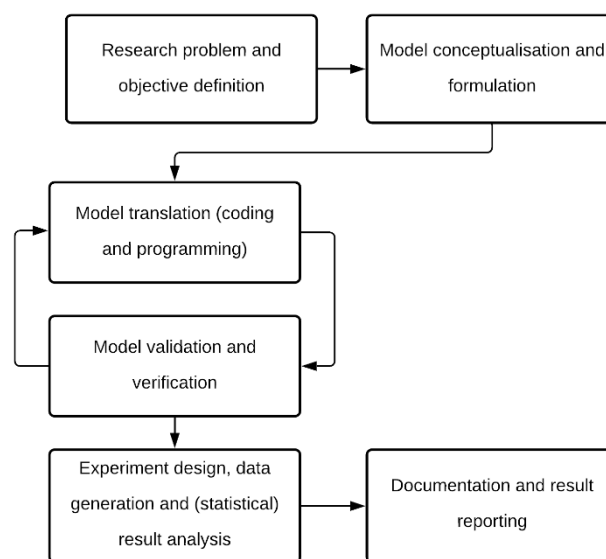
Figure 3.5 Simulation process flow (adapted from Banks et al. (2005), Sterman (2010), and Rossetti (2015))

Pointed by Sterman (2010) and Banks et al. (2005), the processes of simulation studies here are not sequential, but sometimes can be iterative. In this thesis, the simulation processes are also iteratively formed to perform the simulation.

3.4.1 Research problem and objective definition

The first step for simulation studies is to define the research problem and its objective. The problem concerns what will be addressed, while the objective articulates what kind of questions

need to be answered by simulations to tackle the research problem (Banks et al., 2005). According to Rossetti (2015), there are four general objectives for simulation:

1. *Comparison.* Simulations are conducted to compare the performance of alternative systems based on different combinations of factors (the 'factors' here means independent variables).
2. *Optimisation.* It is a special case of *Comparison* where the performance of alternatives is examined and the best is selected.
3. *Prediction.* Simulations are conducted to predict the future behaviours of the system.
4. *Investigation.* Simulations are conducted to explore and obtain understanding and knowledge of the system behaviour given different inputs.

To effectively guide the implementation of simulation, a clearly defined problem should be constructed. According to Sterman (2010), the problem defines the boundary of the research and determines what should be studied as well as excluded. To ensure the appropriate research problem and objective definition, multiple iterations of discussions between the author and the supervisor teams were conducted and the previous relevant literature was followed. After refining iteratively, the problem of this thesis is defined as: how does the influence of online review adoption differ between supply chain configurations, which is **RQ3**. Three configurations of the supply chain are considered in Chapters 4 to 6, and simulations are used to examine how online review adoption can influence the performance of (1) uncapacitated forward supply chain; (2) capacitated supply chain; (3) closed-loop supply chain. The author regards the objective of this study as *Comparison* where in each of the configurations, the performance of the supply chain (measured by supply chain profit) is compared between the scenarios of adopting online reviews and without online reviews, together with different contextual factors.

3.4.2 Model conceptualisation and formulation

A good model should be representative of real-world system. However, as pointed by Sterman (2010), it does not mean simulations should completely 'mirror' the real system but need to reasonably simplify the complexity of it. To conceptualise and formulate a suitable model and answer the research problem, only essential features of the research problem should be extracted while the model assumptions should be developed accordingly (Banks et al., 2005). Also, previous literature suggested that the complexity of the model should be no more than

achieving the purpose of answering the problem (Kelton, 2002; Banks et al., 2005). Therefore, Banks et al. suggested models should be formulated from their simplest form and proceed to include the complexity, which is the logic of the model formulation in this thesis as the three models from Chapters 4 to 6 are from simple to complicated.

In this thesis, the model conceptualisation and formulation are conducted based on the efforts in three aspects. First, previous literature is reviewed to understand the behaviours of both market side system and supply side system from well-developed analytical/simulation work (i.e. APIOBPCS and models for online reviews). Also, multiple tools are used to clarify each system and the relationship of them. Specifically, causal loop diagrams and stock-flow charts are used for supply side system where SD is adopted, and state chart and flow chart are used for market side system where ABM is used. The clarified relationships are then used to construct the mathematical equations. Finally, the observations on real-world practice in E-commerce are used to refine and modify the formation of the new models in this thesis.

3.4.3 Model translation (coding and programming)

After conceptualising the models, the software is needed to translate the conceptual models to computer program. As the complexity of the models usually leads to the high volume and variety of information processed and stored, the flexibility of the software is the main concern as highly flexible software can significantly save time in model coding (Banks et al., 2005). In this thesis, RStudio (rstudio.com) is used as the main simulation software for carrying the model translation. RStudio is an interface editor of R which is a specialised programming language for statistical analysis (Kabacoff, 2011). The reason for choosing R is because it can efficiently cope with SD and ABM through its flexible data frame and array construction. In addition, there are extensions available in RStudio to connect codes with NetLogo (Wilensky, 2006) through a package called RNetLogo (Thiele, 2014), enabling it to construct the highly complicated model.

Apart from the flexibility of RStudio, another reason the author chooses it is due to its power in statistical and numerical analysis. This means the results simulated in RStudio can be directly analysed in the same software. Not only can this save time for modelling and analysis, but the

consistency of the data format reduces the probability of computational error, ensuring the reliability of the results.

The author also compared the capability of RStudio with other frequently used alterative packages. For example, in system dynamics for APIOBPCS simulation, Vensim (Turrisi et al., 2013), MATLAB (Ponte et al., 2020), and Excel (Potter and Lalwani, 2008) are often used. For agent-based modelling and hybrid simulation, AnyLogic becomes popular in recent years. However, when comparing these applications with RStudio, several weaknesses of them can be identified when coping with simulations in this thesis. First, although these packages can probably handle hybrid simulation, they are not flexible enough. For example, Vensim and Anylogic are weak in doing some numerical analysis, such as numerical integral (this will be used in the agent-based modelling in Chapter 6, while Excel is not excellent in processing speed. However, in RStudio, open-sourced packages can perform numerical analysis very well (see Cortez (2014) for a thorough introduction) and at an acceptable speed. Also, these packages do not have rich statistical extensions, while R is excellent in statistical analysis. The convenience and rich functions of statistical analysis in RStudio is essentially the main strength of R, which can not only lead to a quicker analysis, but also save a huge amount of time on model verification. In addition, compared with Vensim, Anylogic, and MATLAB, RStudio is free to access some advanced functions (such as the 'calibration' and 'optimization' in Vensim). Therefore, the author decided to adopt RStudio in this thesis to utilise its advantages. Meanwhile, there can be some disadvantages of RStudio. The first is that the time for learning RStudio in simulation can be longer than Vensim and AnyLogic, as it does not work in the 'drag-and-drop' way. This means RStudio users should put a great amount of time grasping the grammar of R language. Also, there is no simulation process visualisation in RStudio, and simulation can only be done by using the codes (Duggan, 2016). This can increase the time for checking the accuracy of the codes. To overcome it, the author put a significant amount of time into checking and verifying the codes.

3.4.4 Model validation and verification

Model validation and verification are to ensure the models are correct and suitable for the research problems so that the simulation results are accurate and can generate useful insights (Sterman, 2010). More precisely, according to Banks (2005) and Sargent (2013), the validation

of a model is to ensure that the model is representative of the real system and has a satisfactory level of accuracy for its research/application purposes, while the verification is to ensure the model implemented in the software package is correct. To perform validation and verification within the process of model building, four aspects need to be considered (Sargent, 2013; Banks, 1988):

- *Conceptual model validation* is to ensure the **assumptions and theories** to build the model are correct, and the **conceptual model** is representative of the real system and can satisfy its research purposes and answer research problems.

- *Computerised model verification* is to ensure the **model coded in the software** accurately implements the conceptual model.

- *Operational validation* is to ensure the **output** generated from the simulation model is accurate (at an acceptable level) and can fulfil its research purposes.

- *Data validity* is to ensure **data** used in model development, experimentation, and performance examination is adequate and correct.

In Figure 3.6, the relationship between four aspects and model building is presented.
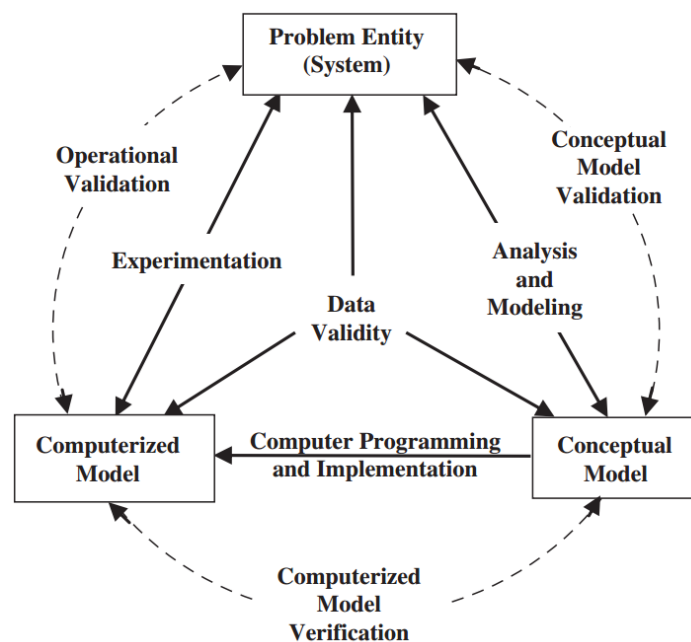
Figure 3.6 Relationship between model building and validation & verification processes (adopted from Sargent (2013))

To effectively conduct the validation and verification from each aspect, multiple techniques in Table 3.7 can be applied. However, as suggested by Banks et al. (2005) and Van Horn (1971), when validating and verifying a simulation model, not all techniques should necessarily be used and the 'cost-to-value' ratio needs to be considered.

Conceptual model validation	Adopted in this thesis
1. Face validity: consult knowledgeable people and experts in the domain to validate the conceptual model	✓
2. Existing knowledge reference: refer to previous studies, observations, experience to validate the conceptual model	✓
Data validity	
1. Historical data comparison: compare input data distribution with the historical data record	✓
2. Existing theory comparison: compare collected data with existing theory (e.g. inter-arrival data should follow exponential distribution)	✗ (Not applicable as no empirical data is used in the thesis)
3. Expert opinion: validate data pattern with experts	✓
4. Screening and outlier evaluation: screen data for outliers and evaluate if they are correct	✗ (Not applicable as no empirical data is used in the thesis)
Operational validation	
1. Existing system comparison: compare model outputs with existing systems or similar ones	✓
2. Expert opinion: validate model output behaviour with experts in the domain	✓
3. Existing knowledge reference: refer to previous studies, reports, observations to validate outputs	✓
4. Historical data comparison: compare outputs with historical data where statistical methods can be applied (i.e. goodness-of-fit test)	✗ (Not applicable as no empirical data is used in the thesis)

5. Multiple runs: operate simulation models multiple times to mitigate the randomness bias ✓

6. Turing test: perform Turing tests to validate the model ✗(Not applicable as no artificial intelligent programming is used in the thesis)

7. Sensitivity analysis: perform sensitivity test through the change of (1) numerical values; (2) behavioural modes; (3) policy implications to validate the model. ✓

Computerised model verification

1. Divide-and-conquer: write and debug codes in each sub-model one by one rather than do them for the whole model just once ✓

2. Peer review: review codes by more than one simulation expert ✓

3. Analytical comparison: compare simulation results with analytical results ✓

4. Trace: display the state of the variables after certain events occur and check if they are consistent with the model logic ✓

5. Degeneracy test: run model with simplified assumptions to check its behaviour ✓

6. Animation: observe animations of the model to verify its accuracy ✗ (This is not adopted as RStudio has no function to automatically animating simulation.)

7. Software package use: using well-developed simulation package to mitigate errors ✓

8. Structure walkthrough: manually check codes line by line ✓

9. Re-programming: program critical sub-models more than once ✓

10. Input value change: change input to different value including its extreme value to check if there is any abnormality in outputs	✓
11. Clear definition: clearly define variables in codes	✓

Table 3.7 Validation & verification techniques overview (adapted from Sargent (2013), Banks et al. (2005); Sterman (2010); Law (2014))

In this thesis, the validation and verification conducted are indicated in Table 3.7. Some techniques related to empirical data are not suitable for the models (e.g. historical data comparison) as this thesis is a computational study without empirical data. Instead, the validity (internal and external) of the model is essentially ensured by the adaption of the well-developed models on both the supply chain side and the market side. As both the supply chain model (i.e. APIOBPCS) and the market side model (i.e. consumer choice model based on customer utility) are widely used in previous research and highly cited in their own field, the conceptual model validity and operational validity of models in this thesis can be guaranteed. For data validity, the values/distributions of parameters and variables are mainly based on highly cited research (see following chapters), with only a few parameter values set based on industrial reports, discussion with supervisors and experts, and analytical reasoning. Therefore, the focus of the validation and verification processes is essentially the computerised model verification. To conduct a sufficient computerised model verification, the author applied all techniques except 'Animation' as the software used is not capable of animating the simulation processes. Therefore, it can be confidently claimed the model is fully verified, and the results are valid and can shed useful insights.

3.4.5 Experiment design, data analysis, and result report

When designing simulation experiments, the first to consider is the type of simulations. Broadly speaking, there are two simulation types, namely terminating simulation and steady-state/non-terminating simulation. Terminating simulation needs to consider the transient period of the system while the steady-state/non-terminating simulation only focuses on the long run and stable performance (Banks et al. 2005). In this thesis, the steady-state simulation is chosen as the suitable design. First, previous research in the supply chain (e.g. Dejonckheere et al., 2004) and online reviews (e.g. Kwark et al., 2014) focus largely on the steady-state performance.

Therefore, adopting steady-state simulation is consistent with the academic tradition. In addition, it is sufficiently reasonable to assume that the E-commerce website traffic is very high, which means customer opinions can converge to the steady state soon after sales start. Even though the product life cycle is not very long, during the life cycle, steady state can be achieved. The author also acknowledges that there is value to study the transient state performance of the system and put it in a future direction in Section 7.5.2.1.

Specifically, the steady-state in this thesis means that the system has experienced enough periods after which the initial condition bias from the supply chain (i.e. initial inventory value) as well as from online reviews (i.e. highly fluctuated online review rating in early periods) can be ignored when evaluating the relevant system performance. Through observing the system, order size and online review ratings become stable after 100 periods in most of the experiments under different parameter settings. Under such a condition, following the Banks et al. (2005) suggestions, the 'warm-up' period is selected as sufficiently long (i.e. 3000 periods). As the total simulation periods are 20000, it can be confident that the transient bias will not pose an influence on the steady-state system performance. Further, multiple runs are conducted to eliminate the randomness bias based on the rule suggested in Kelton (2002).

After selecting the experiment type, the independent variables for the experiments need to be selected. Here, the author would highlight the difference between independent variables and simulation parameters. For the factors considered in ANOVA, they are called independent variables. While for other factors which are assumed as fixed values in the simulation and not considered in ANOVA, they are called parameters. For parameters, not ANOVA but sensitivity analysis is conducted on them. As simulation involves both online reviews and supply chain, many potential factors can be considered as independent variables. However, because the model is computationally costly (especially the model in Chapter 6), only the most relevant factors should be selected as the independent variables to ensure the useful and generalisable insights can be obtained within an acceptable amount of time. The processes of selecting independent variables are supported by previous studies (e.g. Zhao et al., 2002; Lau et al., 2008; Li and Hitt, 2010; Kuksov and Xie, 2010; Cannella et al., 2015, etc.), expert discussion in the international and internal conferences, and the author's analytical reasoning. Apart from the independent variables, the values of simulation parameters are determined by previous studies,

reports, and expert discussion. When necessary, sensitivity analysis for parameters is conducted (see Chapters 4 to 6). For the dependent variable (performance measure), the supply chain profit is selected to follow the mainstream of this domain (see Table 2.4).

To analyse the data and find the relationship between independent and dependent variables, full-factorial experiments are conducted, with their results analysed through ANOVA. In the dynamic simulation research on supply chain management, there are two types of analysis modes. The first mode, such as Chen et al. (2000), Dejonckheere et al. (2004), Tang and Naim (2004), reports the point estimations of the simulation without performing the statistical tests (e.g. ANOVA or t-test). These studies, however, mainly use simulation as numerical analysis to confirm their analytical results. In other words, in such research, the model is analytically solved and is a 'white box'. The second mode, such as Zhao et al. (2002), Xie et al. (2004), Cannella et al. (2008), uses statistical analysis including ANOVA and other *post hoc* tests to analyse data. Compared with the first mode, in these studies, no analytical form of the model is (able to be) given, meaning that the system is a 'black box'. Therefore, the relationship between independent variables and dependent variables (performance measure) is purely reflected from data without the aid of analytical results. Under such a condition, because statistical tests can rigorously analyse data and mitigate subjectivity, they essentially enhance the reliability of the finding of the 'black box' model. Therefore, due to the 'black box' property of the models developed by this thesis, ANOVA is applied to the following chapters.

Finally, to report the results, the results of the experiments are presented by their statistical significance in table format as well as numerical relationship in figure format (see following chapters)

3.5 Research ethics

As this thesis adopts simulation methods to study supply chains, it can be categorised into management science and operations research (MS/OR). Although MS/OR focuses on applied mathematics which is different from other social science fields involving a high level of human participation, as the results of MS/OR can have impacts on human life, conducting MS/OR

research should also be guided and regulated by ethical practices (Gass, 2009). Ethics, according to Saunders et al. (2016), means the standards of research behaviours that guide the ways of conducting research in relation to the rights of research objects or the ones who can be influenced by the research. To ensure the studies conducted in this thesis follow an ethical approach, multiple ethical checks have been conducted, with their introduction below.

First, the author conducted the studies in this thesis under the guidance of Cardiff Business School ethical procedures. The ethical approval is attached in Appendix A3. Second, the author followed Saunders et al.'s (2016, pp.243-245.) ethical principles, cited in Table 3.8. Finally, as this thesis is within MS/OR field, the author also obeyed the ethical guidelines by the Institutes for Operations Research and Management Science (INFORMS) when conducting research. All rules announced in the INFORMS ethical guideline were followed except those applied to empirical data collection, as this research does not contain empirical data. The weblink for the guideline is also attached in Appendix A3.

Ethical principles	
Integrity and objectivity of the researcher	✓
Respect for others	N/A
Avoidance of harm (to participants)	N/A
Privacy of those taking part	N/A
Voluntary nature of participation and right to withdraw	N/A
Informed consent of those taking apart	N/A
Ensuring confidentiality of data and maintenance of anonymity of those taking apart	N/A
Responsibility in analysis of data and reporting findings	✓
Compliance in the management of data	✓
Ensure the safety of the researcher	✓

Table 3.8 Ethical principles of conducting research (Source from Saunders et al. (2016, pp.243-245.)

3.6 Chapter summary

In this chapter, the philosophical stance of this thesis is discussed, followed by the introduction of the simulation methodology. As a commonly used methodology in operations research and management science, simulation has its advantages, especially for problems with nonlinearity, heterogeneity, and analytically intractability.

Through the adoption of hybrid simulation, this thesis integrated online reviews into supply chain modelling which are the two research areas previously studied separately. This chapter starts the development of OR-SCM framework from a macro level, aiming to pave the way for addressing **RQ2**. The following Chapters 4 to 6 will implement this framework to build models and study how the adoption of online reviews can influence supply chain performance between different configurations.

CHAPTER 4

BASE MODEL

4.1 Chapter overview

This chapter starts to apply hybrid simulation to study the influence of online reviews on supply chain performance. A forward uncapacitated supply chain base model is developed to examine how online review adoption can influence supply chain profitability. This chapter forms the answer for part of the **RQ2** and **RQ3**. The supply chain profitability is considered under the influence of three independent variables namely online review adoption, customer estimation on product quality, and supply chain lead time, with the latter two variables as moderators, and the focus here is whether adopting online reviews can bring higher profit to supply chain. Simulation experiments based on agent-based modelling and system dynamics (i.e. APIOBPCS framework) are used as the methodology in this chapter, and rigorous statistical analysis (i.e. ANOVA) is conducted to examine the key main and interaction effects of variables.

As this chapter focuses on how customer feedback on online reviews can influence prospective customer purchase decisions and consequently supply chain profitability, it is a study on *customer-customer information sharing* function of online reviews (Section 2.3.2). Customers, through online review comments, are connected with each other, meaning that this chapter is a realisation of *connecting-tool mechanism* (Section 2.3.3). As a base model, a forward supply chain configuration with one supplier and one retailer is adopted, consistent with structure B in Figure 2.6. Through simulation techniques listed in Section 3.5, the base model is implemented, and open to extensions for Chapter 5 in which supply chain capacities are considered and Chapter 6 in which customer return and closed-loop supply chain operations are added. The connection between each chapter is visualised in the following Figure 4.1.
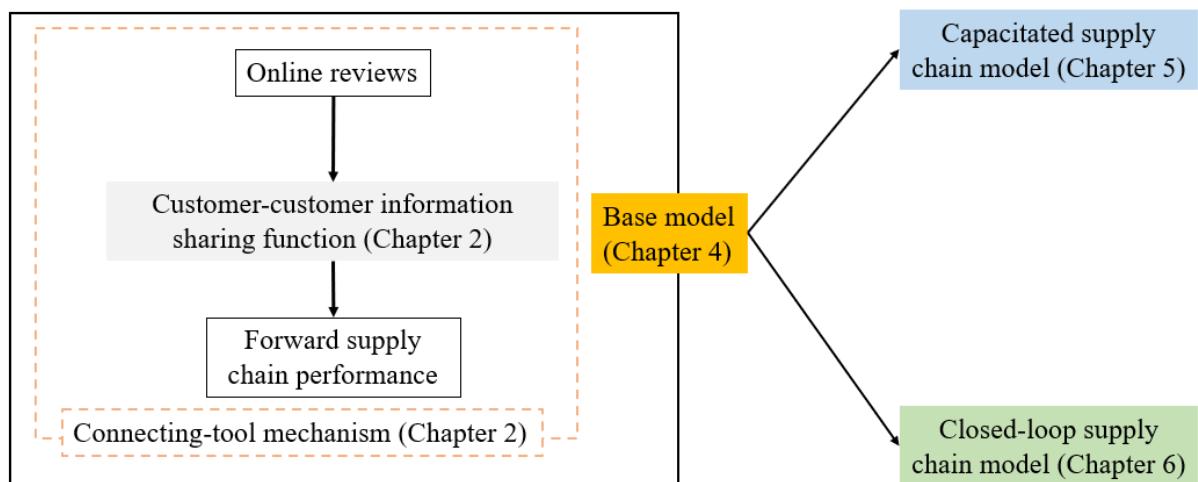
Figure 4.1 The connection between Chapter 4 and other chapters

4.2 Research background: online reviews in supply chain

Online reviews, as a form of 'electronic word-of-mouth' communication, deliver the product evaluations of previous customers and inform future customers (Chen and Xie, 2008). Through online reviews, customers can learn information about product attributes to update their perception and evaluation of products, and make purchase decisions accordingly (Li et al., 2011). Online reviews are therefore an invaluable source of information for customer E-shopping (Chevalier and Mayzlin, 2006).

The influence of online reviews on customer demand and product sales are well-documented in marketing and information management fields (e.g. Purnawirawan et al., 2015; You, et al., 2015), but the research on online reviews for supply chain management, as reflected in Chapter 2, is in its infancy. Although Chapter 2 indicates in supply chain management, scholars have started exploring the influence of online reviews on sales forecasting (e.g. Lau et al., 2018; Chong et al., 2016), product design (e.g. Jiang et al., 2017), and product return (e.g. Minnema et al., 2016), Section 2.3.1 and Table 2.2 show that very few studies consider the influence of online reviews in the supply chain from a systemic perspective, and none of them explicitly focuses on the influence of online reviews on inventory management. As the importance of systemic investigation on online reviews in the supply chain has been confirmed (Kwark et al., 2014) and inventory management is one of the most important supply chain activities and tightly linked to the overall supply chain efficiency (Lee et al., 1997), this gap motivates the

raise of **RQ3**. The author believes filling this gap by answering **RQ3** can inform companies better utilise online reviews in their supply chain management and obtain higher performance. In this chapter, the **RQ3** will be partly addressed.

4.3 Model formulation

In this section, a forward uncapacitated E-commerce supply chain with online reviews is modelled. The model consists of two parts: demand generation and supply. A pictorial description for the base model is presented in Figure 4.2 to compare when this supply chain adopts online reviews and when it does not adopt them. The nomenclature of Chapters 4 to 6 is listed in Appendix 4.
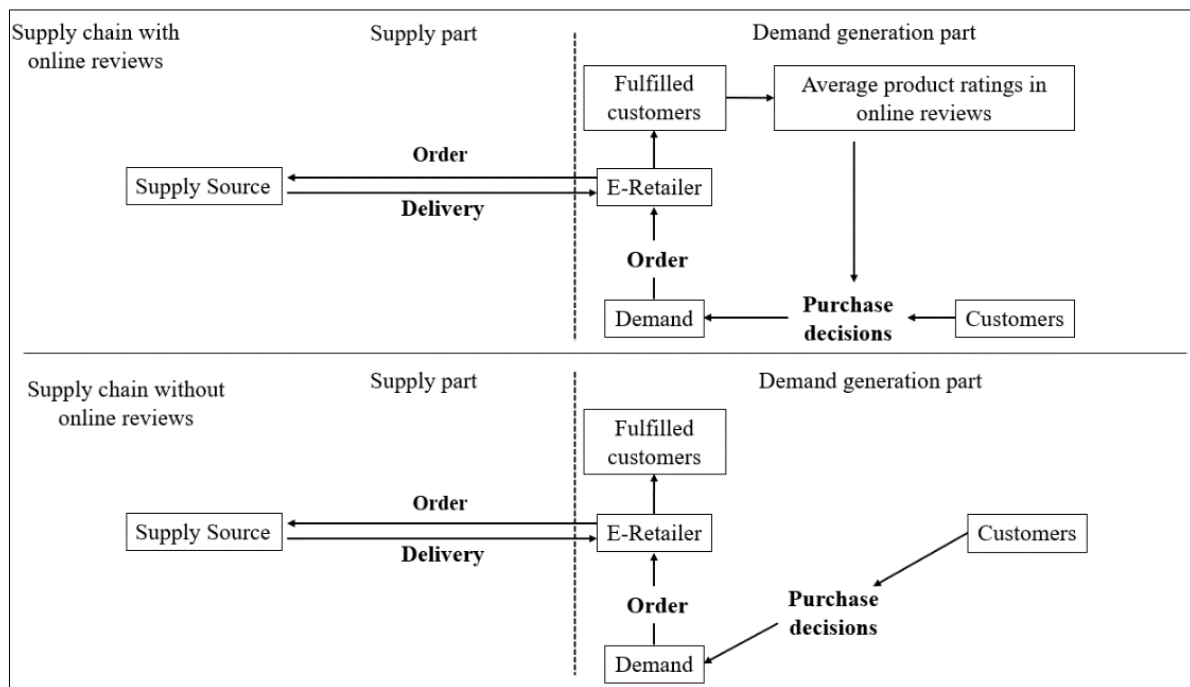
Figure 4.2 A supply chain model with/without online reviews

To illustrate how this represents a supply chain model, as opposed to a dyad, the characteristics of each player are illustrated in Figure 4.3. As can be seen, each echelon of the chain (i.e. customer, supplier, retailer and, in the context of Chapter 6, remanufacturer) is of great importance in the models and cannot be simply merged as a single company. Because of the diversity in the characteristics of different players, considering the models from a perspective of chain rather than dyad is more appropriate.
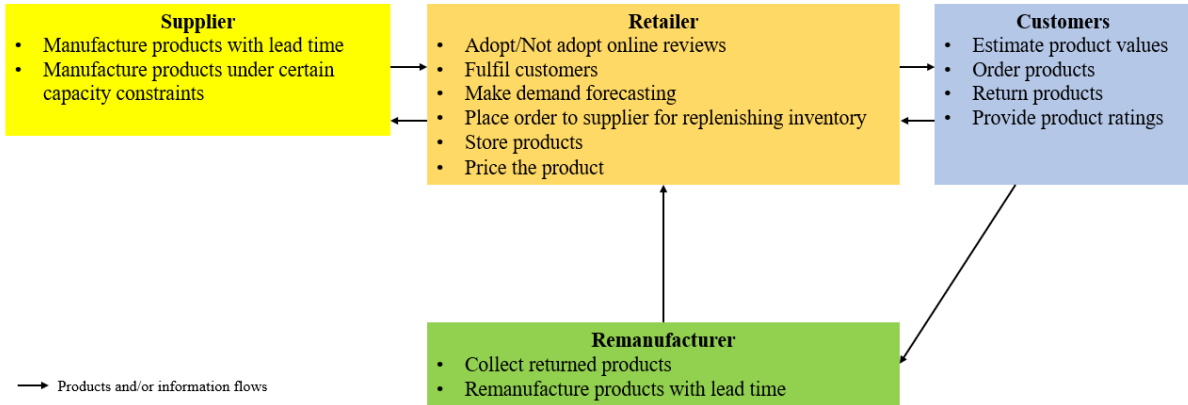
Figure 4.3 Characteristics of each player in the supply chain

4.3.1 Demand generation

This paper starts from modelling demand generation, and it is derived from the established models by Li and Hitt (2008) and Hu et al. (2017). Underlying the decision-making process in these models is the utility gained (or utility lost) from purchasing a product. A product has two attributes, namely search attributes and experience attributes. According to Li and Hitt (2008), as the search attribute can be inspected before purchase (such as size, colour, brand name), the utility derived from the search attribute is only determined by each customer's preference. The utility derived from experience attribute, on the other hand, depends on the quality level of the product, with better quality leading to higher utility. Numerically, the relationship between utility and the product attributes can be expressed as $utility = q + x - p$, where q represents product quality (experience attribute), x represents customer own preference on the product (search attribute), and p represents price (Li and Hitt, 2008).

Based on the above assumption, an agent-based model can be established to model demand generation. The agents, in this model, are the customers coming to the E-commerce platform. The attributes of each agent are their value of quality and preference. The price, p, is not considered as a unique attribute but a fixed number for every agent, as the model focuses on operations rather than pricing decisions of the supply chain. In other words, the online retailer is assumed as a price taker. Each agent is assumed to have multiple and heterogeneous behaviours, including ordering products, posting online reviews, or after purchase behaviours (such as product return in Chapter 6) which will be introduced in the following texts.

Specifically, before purchasing, a customer (which is an agent) coded as i in period t has full knowledge of search attribute, and thus knows the utility derived from it (x_{it}) based on his/her preference, but this agent can only estimate the value of the real product quality (Li and Hitt, 2010). For their estimation on quality, this thesis assumes every customer has the same value (Hu et al., 2017), and this estimation is notated as q^e when there is no online review. Therefore, customer estimated utility (notated as U_{it}^e) before purchasing without online review is $U_{it}^e = q^e + x_{it} - p$. x_{it} is assumed to follow a uniform distribution from 0 to 1, i.e. $U \sim (0,1)$. Without loss of generality, this chapter normalises the utility of the best substitute as 0 (Li and Hitt, 2008), and thus a rational customer will decide to buy the products only if U_{it}^e is greater than 0.

When there are online reviews, customers can see an average rating presented in the review system. Then, the quality estimation will be influenced by the average rating (notated as $\bar{R}_t$) in period t in the review system observed by the customer. The generation of $\bar{R}_t$ will be discussed later in equation (4.3). Here, arguing from the perspective of bounded rationality, Li and Hitt (2008) assume that each customer's quality estimation will be updated equal to $\bar{R}_t$. Based on this, a unified equation for estimated utility U_{it}^e can be proposed as

$$U_{it}^e = \begin{cases} q^e + x_{it} - p, & \text{no review} \\ \bar{R}_t + x_{it} - p, & \text{review available} \end{cases} \tag{4.1}$$

Therefore, when a customer i in period t has their $U_{it}^e > 0$, they will order the product, otherwise they will leave. For the case of no review in equation (4.1), this fits the scenario when the online review system is not adopted. Also, it applies to the first period when the review system is used, as nobody would have posted on the review system in the 'period 0'. There can also be some special cases (for example that nobody posts a review in the first period), causing no review to be available in the second period. In this special case, the equation for no-review-condition will always apply until reviews are posted by customers.

After purchasing and receiving the product, the real utility (U_{it}) for customer i in period t after consuming the product is

$$U_{it} = q_{it} + x_{it} - p \qquad (4.2)$$

where q_{it} is the real product quality. Based on Li and Hitt (2008), this thesis assumes q_{it} follows a symmetric $Beta(1,1)$ distribution, which is mathematically equivalent to a uniform distribution i.e. $q_{it} \sim U(0,1)$. It can be seen from the next paragraph discussion as well as equation (4.3) that no impact on the results is generated from the selection of the parameter of symmetric Beta distribution, as the mean values of all symmetric Beta distributions are equal to 0.5. In addition, this thesis assumes q_{it} and x_{it} are not correlated with each other (Li and Hitt, 2010; Papanastasiou, and Savva, 2017; Kuksov and Xie, 2010).

Also, as the real quality distribution is assumed as $q_{it} \sim U(0,1)$, the mean of real quality $E(q_{it})$ is thus 0.5. However, it is rare that customers will correctly estimate the mean quality before purchase for various reasons. On the one hand, when customers face unfamiliar products, they can under-estimate the real quality of them (Li and Hitt, 2008). On the other hand, the products may also be excessively advertised (Shen et al., 2018), leading customers to over-estimate product real quality. Therefore, it is more sensible to consider the adoption decisions under these two biased estimation scenarios instead of assuming customers can accurately estimate the mean real quality. Based on this thought, this thesis considers the situations of under-estimated quality and over-estimated quality scenarios, respectively. According to Li and Hitt (2008), the q^e is assumed as 0.3 for the under-estimation scenario. Symmetrically, this thesis chooses q^e as 0.7 when quality is over-estimated. In other words, the over-estimation case means $q^e > E(q_{it})$ while the under-estimation case $q^e < E(q_{it})$. The details for quality estimation are in the experiment design (Section 4.4).

For those customers who order the products ($U_{it}^e > 0$) and are fulfilled by the retailer, they experience the products and obtain q_{it}. If an online review system is used, reviews can be posted. If customer i is willing to post their product rating, *their individual post value will be equal to q_{it}* (Li and Hitt, 2008). For those customers not willing to post, no rating is recorded. To model this behaviour, this chapter assumes the probability of each customer posting reviews equal to 0.1 (Bhole and Hanna, 2018). The E-commerce system will generate the rating for the next period, i.e. $\bar{R}_{t+1}$, through averaging all individual posted values ranging from period 1 to t, which means $\bar{R}_{t+1}$ are bound in 0 to 1 for any $t > 1$:

$$\bar{R}_{t+1} = \frac{sum\ of\ all\ posted\ rates\ from\ period\ 1\ to\ t}{number\ of\ posts} \qquad (4.3)$$

Consistent with Jiang and Guo (2015), Hu et al. (2017), and Li and Hitt (2008), this chapter assumes that the frequency of updating the review is one period, which means that customers arriving in the same period t will see the same online review value $\bar{R}_t$, and the rating posted in period t will be used to update $\bar{R}_{t+1}$. Therefore, for customers arriving in period t, all of them will use $\bar{R}_t$ to estimate their own q_{it} (i.e. $U_{it}^e = \bar{R}_t + x_{it} - p$).

Because of the supply chain replenishment policy as well as the stochasticity of the demand, sometimes stock-outs can occur, and customers cannot be fulfilled. When it happens, this chapter assumes that customers who cannot be fulfilled will leave. In other words, no back-order is allowed and unfulfilled customers will become lost sales (Turrisi et al., 2013; Dominguez et al., 2018). This is because, E-retailing is almost a perfectly competitive market, if customers cannot be fulfilled immediately, usually they can directly turn to other substitutes without waiting. Also, some platform systems do not give customers a chance to wait. For example, the online system of UK grocery giant ASDA (asda.com) occasionally will not tell customers about stock-out until the moment for the fulfillment, even though the customers have already paid. If the stock-out occurs, the system will automatically cancel the order and refund the customers, directly leading to lost sales. Under such a case, waiting is impossible.

Finally, it is worth noting that the property of the products modelled in this thesis. First, based on the description in Chapter 1, the products that this thesis focuses are the items provided through B2C E-commerce supply chain. Also, the products are the 'experience products' (Kuksov and Xie, 2010; Li and Hitt, 2008) whose quality cannot be fully inspected by customers before purchase. In other words, before purchase, the quality remains uncertain to customers and they only have incomplete knowledge about it, which indicates the customers need to seek more information from online reviews. For example, in practice, the fast fashion goods, books (including e-books), and laptops which are sold online can fit this model.

4.3.2 Supply chain modelling

After modelling the demand process, the supply side of the model can be formulated. Here, system dynamics is adopted, and the well-developed APIOBPCS archetype is utilised (see Table 3.5 for the representative studies). First, in every period, customers visit the E-commerce site. Consistent with Jiang and Guo (2015) and Li and Hitt (2008), this chapter assumes the customer numbers are the same in each period and notated as N. For those customers with expected utility greater than 0, they will order products online, with others leaving. Therefore, the period t demand D_t can be derived as

$$D_t = \sum_{i=1}^{N} f(U_{it}^e), where \ f(a) = \begin{cases} 0, a \le 0 \\ 1, a > 0 \end{cases} \tag{4.4}$$

After observing the demand, the company will use available inventory to fulfil the orders. The available inventory consists of the products on hand in the previous period, I_{t-1}, as well as newly arrived products ordered L period ago, O_{t-L}, where L here is the replenishment lead time. The fulfilled demand which is the company's sales volume is notated as D_t^*, thus:

$$D_t^* = min \ (O_{t-L} + I_{t-1}, D_t) \tag{4.5}$$

After receiving the newly arrived products and fulfilling customers, the inventory level as well as work-in-process in period t of the company is updated as:

$$I_t = max \ (I_{t-1} + O_{t-L} - D_t, 0) \tag{4.6}$$

$$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-L} \tag{4.7}$$

To order new products and replenish inventory, the company needs to make a forecast. This chapter adopts the widely used simple exponential smoothing method to produce the forecasts F_t for period $t + 1$ (e.g. Potter and Lalwani, 2008):

$$F_t = \theta * D_t + (1 - \theta) * F_{t-1} \tag{4.8}$$

It is assumed that although the company loses the unfulfilled customers, the demand information of D_t are still available to the company, which is consistent with previous research

(e.g. Cannella et al., 2017). θ here is the smoothing parameter and according to Syntetos et al. (2011), θ is specified as 0.2.

Finally, based on forecasting, inventory level, and work-in-process level, the company will place an order with negative value not allowed.

$$O_t = max\big((L + 1) * F_t - I_t - WIP_t, 0\big) \tag{4.9}$$

It should be noted that equation (4.9), together with the ordering rules in Chapters 5 and 6, follows a variant of APIOBPCS (i.e. APvIOBPCS). The reasons why the original APIOBPCS is not adopted are twofold. On the one hand, according to Dejonckheere et al. (2003), APvIOBPCS is commonly used in practice. On the other hand, original APIOBPCS needs to specify the target inventory level based on demand distribution information. If the demand distribution is known, the target inventory level is easy to calculate (e.g. based on well-known newsvendor model). However, in this thesis, especially in Chapter 6, the demand distribution is hard to be analytically tractable. If APIOBPCS is adopted, the calculation of target inventory level becomes not operatable due to the unknown distribution. Thus, using APvIOBPCS can essentially make the assignment of the value of target inventory level more operatable compared with APIOBPCS.

Moreover, by selling products the supply chain can obtain revenue but also generate supply chain related costs. This chapter assumes that the supply chain will have holding cost, lost sales penalty, and cost for producing each product. Consistent with Ketzenberg et al. (2000), Hill (2007), and Metters (1997), this chapter assumes there is no ordering cost in the model. The simulation results also support the robustness of this assumption as the order numbers in each simulation experiment are very close, with around 1% difference between the maximum and the minimum number of orders across all simulation experiments. The occurrence of holding cost, lost sales penalty, and cost for producing each product is defined as follows:

- Holding cost: one unit of holding cost will occur if one product is stored in one period.

- Lost sales penalty: one unit of lost sales penalty cost will occur if one customer is unfulfilled, and it is equal to the sum of the loss of profit margin and other intangible costs caused by lost sales.

- Cost for producing each product: one unit of cost for producing each product will occur if one product is manufactured by the supplier. Such a cost includes the raw materials used as well as the cost of capital used for production.

To achieve an exhaustive research design, this thesis sets product price as 1 per unit, which leads the positive sales but not covers the whole market for all scenarios. This thesis adopts the weekly cost structure put forward in Metters (1997), where profit is calculated on the basis of revenue, holding cost and lost sales penalty. Revenue is derived from the sales price, minus the cost for producing each product which consists of production cost and cost of capital used for production. Metters (1997) specifies that the price is 40% higher than production cost, while the annual cost of capital is 13%. This latter figure gives a weekly cost of capital of 0.25% (i.e. $\frac{13\%}{52\text{weeks}}$) of the production cost for one unit, which equates to a weekly discount factor of 0.9975 (i.e. 1-0.25%) (Metters, 1997). As the lead time is assumed ranging from two, four, and eight periods (see Section 4.4), this thesis calculates a one-/three-/seven-period cost of capital for each product (there is an extra period for reviewing orders, see Dejonckheere et al., 2003). As the sales price is set as 1 per unit and, using the relationships expressed in Metters (1997), it has been found that no matter the lead time is short or long, their costs for producing each product are very close to 0.7 (i.e. $\frac{1}{1+40\%} * \left(1 + \left(1 - 0.9975^{lead\ time-1}\right)\right) \approx 0.7$). Therefore, the cost for producing each product is reasonably assumed as 0.7.

Also, consistent with Metters (1997), the ratio of annual unit holding cost to the cost for producing each product is 0.33. Such an assumption from Metters (1997) is consistent with literature (e.g. Zhao et al., 2002) as well as real-world practice where the annual inventory cost per item is usually around 20% or 30% of the unit cost (Tuovila, 2020). Based on the cost for producing each product being equal to 0.7, the holding cost per unit per period is calculated as 0.0045, which is obtained by $0.7 * \frac{0.33}{52\text{weeks}}$. Furthermore, sensitivity analysis is also conducted (see Section 4.7) to the unit holding cost, and the analysis shows our simulation results are robust to the holding cost assumptions.

Finally, the unit lost sales penalty is assumed as 50% of unit cost for producing each product (Metters, 1997), leading to the value of it as 0.35. The lost sales penalty here is defined as the sum of the loss of profit margin together with other intangible costs caused by lost sales (Lodree, 2007; Metters, 1997). When the unit lost sales penalty is 0, it means the cost for lost sales is only the loss of profit margin. However, when the penalty is more than 0, it means other costs can occur. To explain such costs in the context of E-commerce, Xiao and Xu (2018) reported that the online platforms (such as Amazon and Staples Inc.) will penalise retailers for lost sales and unfulfilled orders. Such penalties are imposed if retailers fail to meet a defined fulfilment level, and may be financial or through restrictions on selling privileges. Such kind of penalisation essentially largely increases the cost of lost sales and can even make it significantly higher than the profit margin of the products. Also, customers can penalise the retailer for unfulfillment (Lodree, 2007). For example, a customer subscribing to the premium membership of the online retailer may cancel their subscription following a failure to fulfil an order, which causes profit loss for the retailer. As these scenarios can significantly increase the cost of lost sales, this thesis thus follows Metters (1997) and assume the situation of lost sales penalty greater than 0 to make the model more realistic. What should be noticed here is that based on the sensitivity analysis on unit lost sales penalty, the results are robust to the change of the value. Also, in Chapters 5, different values of lost sales penalty are considered.

All the values of parameters are listed in Table 4.1. Therefore, the profit can be derived as follows:

$$Total\ Profit = Total\ Revenue - Total\ Holding\ Cost - Total\ Lost\ Sales\ Penalty$$

(4.10)

where each term is defined as:

$$Total\ Revenue = (Price - Unit\ Cost\ of\ producing\ a\ product) * Total\ sold\ Units$$

$$Total\ Holding\ Cost = Unit\ Holding\ cost * Total\ holding\ Units$$

$$Total\ Lost\ Sales\ Penalty = Unit\ Lost\ sales\ penalty * Total\ Lost\ sales$$

Equation (4.10) indicates that the total cost for producing products is embedded into the total revenue. It essentially means that the model assumes the total revenue here is the revenue of the whole supply chain (i.e. both supplier and retailer) instead of the retailer's revenue only.

In other words, the simulation experiment examines how the adoption of online reviews can influence the whole supply chain profitability rather than the performance of the retailer. Such a view is consistent with previous literature (e.g. Metters, 1997). The reasons for doing so are twofold. First, considering the influence of online reviews on the performance of the whole supply chain instead of the retailer alone can generate a systemic evaluation of the relationship between online review adoption and supply chain profitability. This essentially fills the gap mentioned in Chapter 1. Second, there are many studies validating that the centralised supply chain can perform better than the decentralised supply chain (Kanda and Deshmukh, 2008; Chen, 2003). Therefore, considering the influence of online reviews on the whole supply chain instead of on the retailer alone can probably avoid the generation of potential misunderstandings and suboptimal insights. Such a kind of systemic consideration of the influence of online reviews on the whole supply chain might introduce another promising direction concerning how the profits of the whole supply chain can be allocated to the supplier and the retailer when online reviews are adopted (e.g. the design of profit-sharing contract).

4.4 Experiment design

The information of parameters, independent variables, and the performance measure is presented in Table 4.1. In this chapter, the variables from the customer side and supply side are considered in the simulation experiments. The main independent variable is online review adoption in the supply chain, including {adopting, not adopting}. Apart from that, the other two independent variables are also taken into consideration. From the customer side, one variable is quality estimation (i.e. q^e). As stated above, customers can over-estimate or under-estimate the product quality before purchase due to insufficient information. Therefore, q^e considers two scenarios as {Over-estimation, Under-estimation} which are equal to {0.7, 0.3}. From the supply side, another independent variable is the length of lead time (L) with three levels, namely {Short, Medium, Long} which are quantified as {2, 4, 8} respectively. The reason why lead time is chosen as a variable is that previous literature indicates its importance in influencing supply chain performance (e.g. Lee et al., 1997; Cannella et al., 2018). Therefore, it is necessary to check if the different values of lead time can moderate the influence of online review adoption on supply chain performance. Although in the supply side, the smoothing parameter for forecasting (i.e. θ) is also important, as this thesis does not focus on how

forecasting methods influence the performance of the supply chain, α is assumed as a fixed value but not considered as a variable in simulation consistent with Syntetos et al. (2011).

Parameters

q_{it}: real product quality	$U \sim (0,1)$
x_{it}: customer preference	$U \sim (0,1)$
p: product price	1
θ: forecasting smoothing parameters	0.2
N: customers each period	50
Unit cost of producing each product	0.7
Unit holding cost (i.e. holding cost per product each period)	0.0045
Unit lost sales penalty	0.35
Probability of posting reviews	0.1

Independent Variables

Online review adoption	{Adopt; Not adopt}
Product quality estimation (q^e)	{0.3 (Under-estimated); 0.7 (Over-estimated)}
L: lead time	{2 (Short); 4 (Medium); 8 (Long)}

Performance Measure

Total Profit

Table 4.1 Experiment parameters and variables for the base model

A full factorial experimental approach is adopted based on the combinations of independent variables, where the total number of experiments is $2 * 2 * 3 = 12$. For each experiment, 20,000 periods are simulated with the first 3,000 as warm-up periods. Five replications are conducted for each experiment, leading to 60 replications in total. Based on the suggestions of Yang et al. (2011) and Cannella et al. (2018), to reduce the effect of randomness, the

replications should be high enough to meet the criterion that in each experiment the half-width 95% confidence interval of the measure is lower than 10% of its mean. As the simulation period is very long, such criterion can be easily met with five replications in the simulation conducted in this chapter. The R codes for simulation are attached in Appendix A1, and the total running time is approximately two working days. The simulation results are then analysed using Analysis of Variance (ANOVA). The Shapiro-Wilk test and Levene's test are conducted to check the assumptions of normality and homogeneity of variance, and no violation of the assumptions is found.

4.5 Simulation verification

The simulation is built in R programming language using RStudio. A thorough verification for the simulation model is conducted using the techniques mentioned in Table 3.7 in Chapter 3. For example, the logic of the mathematical model is based on previous models and real-world situations (e.g. Dejonckheere et al., 2003, Li and Hitt et al., 2008), and the interim findings were presented in international conferences with feedback sought. To verify the model implementation process, the model is divided into different sub-models. For example, for the part of the supply chain model, the output results generated by simulation are compared with the results in Dejonckheere et al. (2004) and no statistically significant difference under p-value equal to 0.05 exists, meaning the modules are of good accuracy. For demand side modules, the author compared simulation and analytical results, with no statistically significant difference found between the two under p-value equal to 0.05. In addition, the author also uses Excel sheets and hand calculations when necessary to triangulate the accuracy of simulation codes. Therefore, the author believes that the model has good accuracy.

4.6 Simulation results

The ANOVA results in Table 4.2 show that all independent variables have significant main and interaction effects on supply chain performance (profit) with a confidence level of 95%. As this paper seeks to study the influence of online reviews in supply chain performance, the analysis below only focuses on the main and interaction effects involving the online review adoption variable.

Variables	Df	Sum Sq	Mean Sq	F value	p value
OR	1	$2.17*10^6$	$2.17*10^6$	25.52	<0.01
QE	1	$3.95*10^{10}$	$3.95*10^{10}$	$4.64*10^5$	<0.01
LT	2	$4.44*10^7$	$2.22*10^7$	261.20	<0.01
OR*QE	1	$3.90*10^{10}$	$3.90*10^{10}$	$4.59*10^5$	<0.01
OR*LT	2	$5.44*10^5$	$2.72*10^5$	3.20	0.0497
QE*LT	2	$9.18*10^6$	$4.59*10^6$	53.97	<0.01
OR*QE*LT	2	$1.34*10^7$	$6.68*10^6$	78.63	<0.01
Residuals	48	$4.08*10^6$	$8.50*10^4$		

Remarks: abbreviation meaning

OR: online review adoption; LT: lead time; QE: quality estimation

Table 4.2 ANOVA results for base model

In Figure 4.4, the main effect of online review adoption is presented. It can be directly identified from the figure that adopting online reviews can bring slightly higher profit to the supply chain than without them. In other words, without considering the effects in different customer quality estimations and different lengths of replenishment lead time, the influence of online reviews on supply chain profitability is not very dramatic, even though such influence is statistically significant.
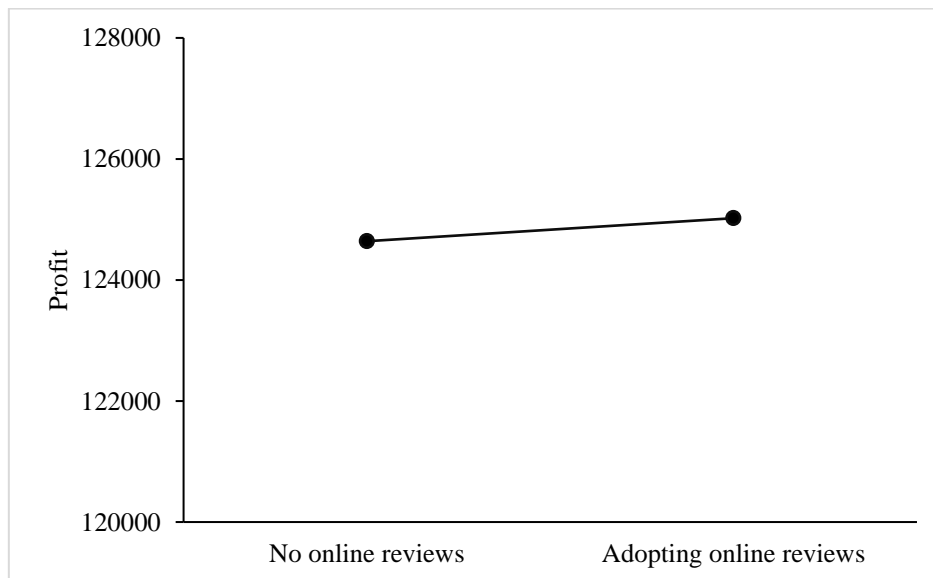
Figure 4.4 Main effect of online review adoption in base model

In Figure 4.5, two interaction effects between online reviews and quality estimation as well as between online reviews and lead time are depicted. Although statistically speaking, both interaction effects are significant, the quality estimation interaction effect is stronger than lead time interaction effect. For two different quality estimation scenarios (i.e. over-estimation and under-estimation), the influences of online reviews on supply chain profitability are opposite. Specifically, when customers have over-estimation bias, online review adoption can decrease the supply chain profit; conversely it can increase the profit if customers have under-estimation bias. For different lead time scenarios (i.e. long, medium, and short lead time), adopting online reviews can all lead to slightly higher profit. However, compared with quality estimation interaction effect, the influence of online reviews from lead time interaction effect on profit looks much smaller, although it can be found that the difference between adopting and without online reviews is higher when lead time is longer.

(a) Quality estimation interaction effect

(b) Lead time interaction effect
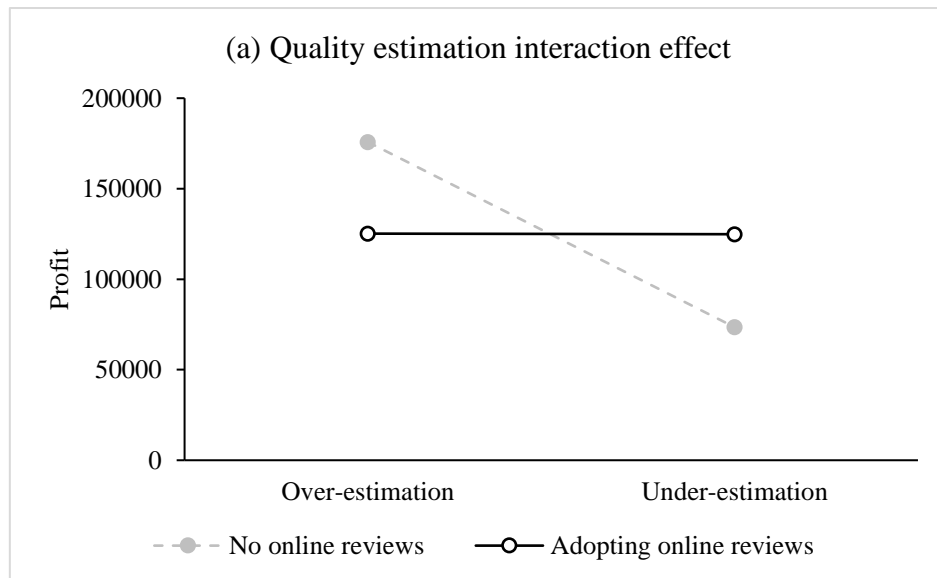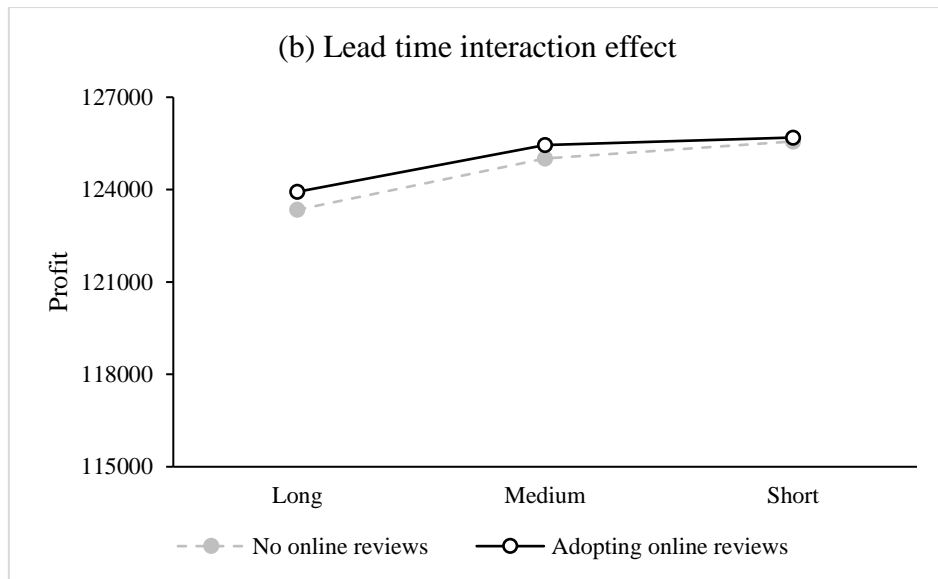
Figure 4.5 First order interaction effects in base model

Finally, in Figure 4.6, the second order interaction is presented, which behaves very similar to quality estimation interaction effect. In other words, when customers over-estimate the product quality, adopting online reviews result in less profit; when customers under-estimate the quality, online reviews can increase profitability. This again indicates the quality estimation interaction effect is more significant than lead time interaction effect, thus different quality estimation scenarios dominate the influence of online review adoption on supply chain profitability.
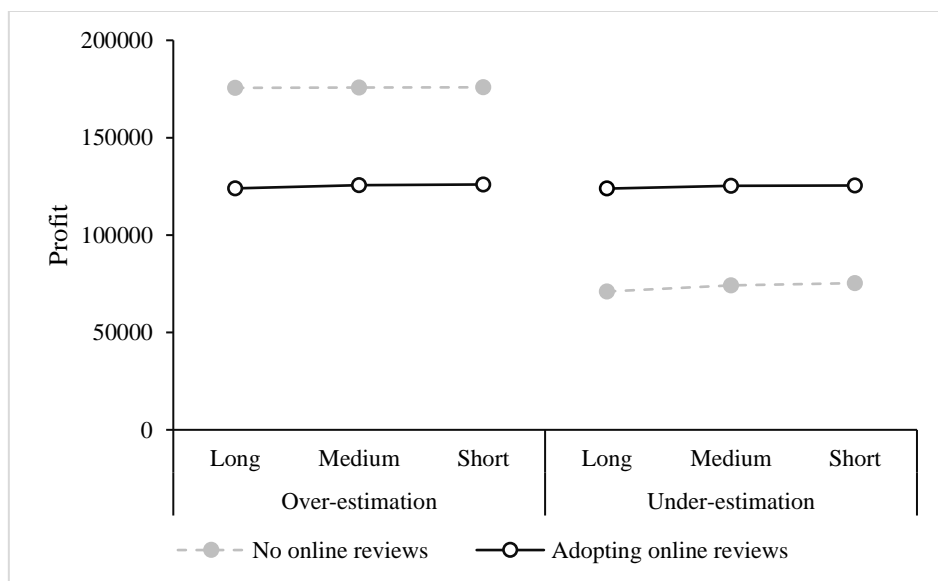
Figure 4.6 Second order interaction effect in base model

To explore the underlying relationships of how online reviews influence the supply chain profitability, a revenue-cost analysis is conducted and presented in Table 4.3 to compare the effects of the adoption of online reviews on the changes of total revenue, total holding cost, total lost sale penalty cost. The difference value between adopting and without online reviews is calculated by using the value of each term when online reviews are adopted minus the value without adopting them. Therefore, if a value is positive (negative), it means under such a scenario, adopting online reviews increases (decreases) this value. Based on the revenue, profit and costs in equation (4.10), a further relationship can be worked out as: the total profit difference is equal to the total revenue difference minus total holding cost difference and minus total lost sale penalty difference.

	Over-estimation			Under-estimation		
	Long lead time	Medium lead time	Short lead time	Long lead time	Medium lead time	Short lead time
Total Revenue Difference	**-51537.06**	**-50915.22**	**-50663.22**	**52154.10**	**51294.30**	**50876.04**
Total Holding cost Difference	-676.84	-760.68	-759.94	616.31	735.52	761.34
Total Lost sale penalty Difference	819.70	45.22	0	-1309.63	-503.51	-40.18
Total Profit Difference	-51679.92	-50199.76	-49903.27	52847.41	51062.28	50154.87

Remarks: Bold numbers are those with absolute values greater than 10000 in revenue and costs.

Table 4.3 Revenue-cost analysis based on difference value in base model

The analysis result in Table 4.3 indicates that, online reviews can decrease total revenue and total holding cost but can increase total lost sale penalty when customers over-estimate the product quality. On the contrary, when customers under-estimate the product quality, adopting online reviews result in revenue and holding cost increase but lost sale penalty decrease. However, although using online reviews can bring changes in holding cost and lost sale penalty, such changes are minor compared with the change in revenue. Therefore, the effect on revenue change led by online reviews, compared with the effects on holding cost and lost sale penalty, dominates the process of supply chain profit-making. This means that the influence of online

reviews on the supply chain profitability is to influence customer quality estimation and demand generation. This is consistent with intuition. Intuitively, companies will try to make customers feel positive about the product so that they can win more demands. The results here show that more demands can be won by adopting or not adopting online reviews in different scenarios, and more profit can be made from the demand increase.

4.7 Sensitivity analysis

In order to test the robustness of the simulation results to the change of parameters, sensitivity analysis is conducted by varying the value of unit holding cost and unit lost sales penalty. Although the value for unit holding cost and unit lost sales penalty is based on Metters (1997), it can be argued that for different types of product, the value of both can vary. Therefore, a sensitivity analysis of them is necessary. First, for unit holding cost, the original value in simulation experiments is 0.0045. The sensitivity test is carried out by assuming the value of unit holding cost as 0 (-100%) and 0.009 (+100%). For the unit lost sales penalty, as the original value is 0.35, the sensitivity test is carried out using 0 (-100%) and 0.7 (100%).

		Unit holding cost	Adopt	No	Profit difference %	Adopt decisions
Under-estimation	Long lead time	0.0045	123988	175668	-29%	No
		0	125998	178355	-29%	No
		0.009	121978	172981	-29%	No
	Medium lead time	0.0045	125578	175778	-29%	No
		0	127494	178454	-29%	No
		0.009	123662	173101	-29%	No
	Short lead time	0.0045	125973	175876	-28%	No
		0	127891	178554	-28%	No
		0.009	124054	173198	-28%	No
Over-estimation	Long lead time	0.0045	123868	71021	74%	Adopt
		0	125873	72410	74%	Adopt
		0.009	121863	69632	75%	Adopt
	Medium lead time	0.0045	125308	74246	69%	Adopt
		0	127220	75422	69%	Adopt
		0.009	123396	73069	69%	Adopt
	Short lead time	0.0045	125411	75256	67%	Adopt
		0	127320	76404	67%	Adopt
		0.009	123501	74108	67%	Adopt

		Unit lost sales penalty	Adopt	No	Profit difference %	Adopt decisions
Under-estimation	Long lead time	0.35	123988	175668	-29%	No
		0	124894	175754	-29%	No
		0.7	123082	175581	-30%	No
	Medium lead time	0.35	125578	175778	-29%	No
		0	125623	175778	-29%	No
		0.7	125533	175778	-29%	No
	Short lead time	0.35	125973	175876	-28%	No
		0	125973	175876	-28%	No
		0.7	125973	175876	-28%	No
Over-estimation	Long lead time	0.35	123868	71021	74%	Adopt
		0	124750	73212	70%	Adopt
		0.7	122986	68829	79%	Adopt
	Medium lead time	0.35	125308	74246	69%	Adopt
		0	125356	74797	68%	Adopt
		0.7	125260	73694	70%	Adopt
	Short lead time	0.35	125411	75256	67%	Adopt
		0	125411	75296	67%	Adopt
		0.7	125411	75216	67%	Adopt

Remarks:

1. Profit difference% $= (\text{Value}_{\text{Adopt}} - \text{Value}_{\text{No}})/\text{Value}_{\text{No}}$;

2. Profit difference% $>2.5\%$: Adopt; Profit difference% $<-2.5\%$: No; Profit difference% within $\pm 2.5\%$: Indifference

Table 4.4 Sensitivity analysis for unit holding cost and unit lost sale penalty

Table 4.4 compares the online review adoption decisions between the original simulation and the situations with varied unit holding cost and unit lost sale penalty. To check if the simulation results are sensitive to the change of unit holding cost and unit lost sales penalty, it just needs to compare if the adoption decision in each experiment in simulation is the same as in the sensitivity analysis. For example, to check if the result is sensitive to the change of unit holding cost when quality is over-estimated and when lead time is short, what should be compared is if the adoption decision in this experiment is the same when unit holding cost is 0.0045, 0 or 0.009. As the three decisions are all 'Adopt', it indicates the result is not sensitive to the change of unit holding cost when quality is over-estimation with a short lead time. Specifically, adoption decisions are defined as three options. If the percentage of profit difference between adopting and not adopting online reviews is within $\pm 2.5\%$, the adoption decision is indifferent.

If the profit difference is above 2.5%, the decision is 'Adopt', while the decision is 'No' when the profit difference is below -2.5%. It can be found, compared with all the results in the original simulation, the sensitivity analysis results present no difference, and the findings are qualitatively held. Therefore, it can be concluded that the simulation results are robust.

4.8 Discussion

In this section, the results as well as the formation of simulations are discussed, which partly addresses **RQ2** and **RQ3**.

4.8.1 Discussion on simulation results

The mechanisms summarised in Chapter 2 suggest that the influence of online reviews examined in this chapter is essentially a realisation of *connecting-tool mechanism*. In other words, in the chapter, online reviews are modelled as a tool to enable more effective communication between customers to exchange quality information (see the definition of 'connecting-tool mechanism' in Section 2.3.3.1), and such communication eventually leads to the performance change in the supply chain. Specifically, the results in Section 4.6 indicates the influence of online reviews in supply chain profitability is mainly derived from changing demand and consequently revenue. Figure 4.7 summarises the simulation results, presenting the causal relationships about how online reviews can influence supply chain performance.
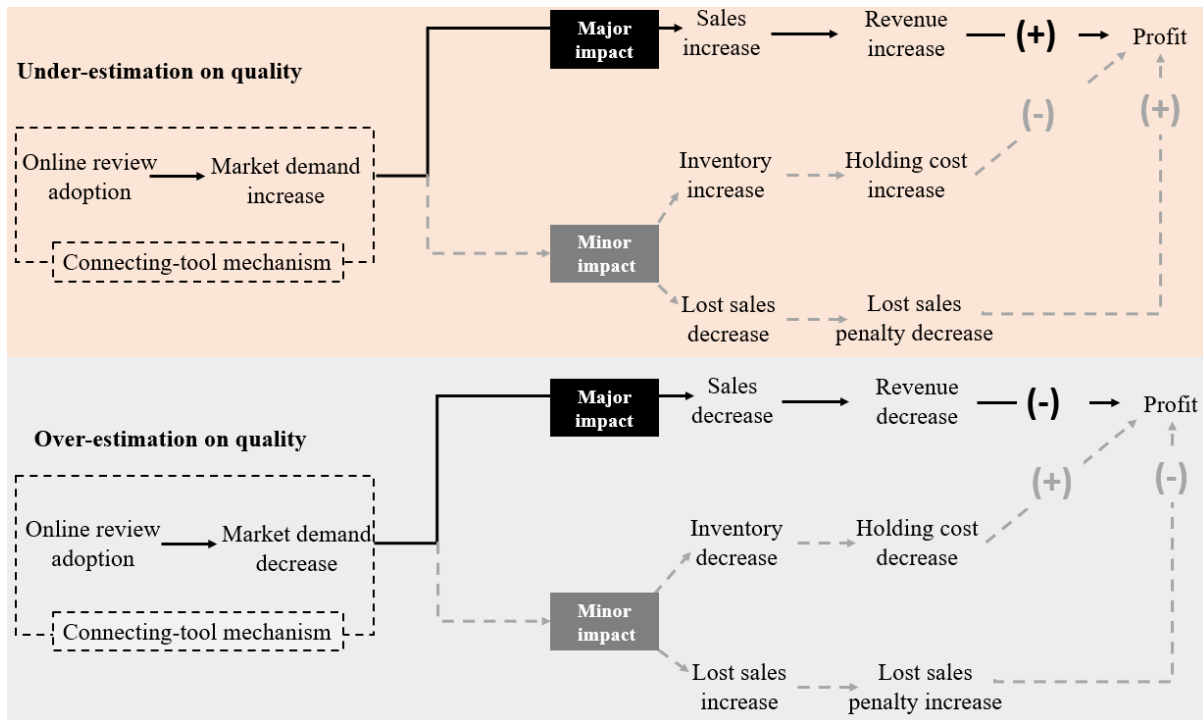
Figure 4.7 Influence of online reviews on supply chain performance

The major impact that online reviews pose on supply chain profitability is their influence on demand and consequently sales and revenue. When quality is under-estimated, online review adoption corrects the estimation bias and increases the customer demand and thus sales. On the contrary, the adoption of online reviews decreases sales when quality is over-estimated. Meanwhile, the adoption of online reviews also works on the change of inventory holding cost and lost sales penalty (Table 4.3). However, compared with the influence on sales, the influence of online reviews on the change of total holding cost and total lost sales penalty is minor. This indicates that under the assumption of this model, online reviews pose a stronger influence on sales rather than supply chain operations. To sum up, and to contribute to the answer to **RQ3**, the influence of online reviews in Chapter 4 model is summarised as follows:

> *In an uncapcitated forward supply chain, online review adoption significantly influences supply chain profitability by changing total supply chain revenue, and such influence is moderated by customer quality estimation.*

The results inform managerial implications for companies that when customers under-estimate the product quality, companies should adopt online reviews but not adopt them when customers

over-estimate the quality. Apart from this implication, the results also illustrate that the online review adoption decision is less sensitive to the length of lead time. Although previous literature (Lee et al., 1997) indicates that the lead time reduction can increase the efficiency of the supply chain, it *moderates* little on online review influence on supply chain profitability. In other words, when companies consider whether they need to adopt online reviews, they may not need to consider the lead time effect in the first place.

Although the results and implications drawn from simulations look straightforward, the online review effects on supply chain side operations (i.e. holding cost and lost sales penalty) should not be ignored directly, because it can be identified that the adoption of online review does lead to some changes on them based on Table 4.3. The reason why such influences are not visible on them is that the supply chain in this chapter is an uncapacitated system without product return. In the following Chapters 5 and 6, the thesis will show that the decisions on the adoption of online reviews will not just rely on customer quality estimation but also contingent on other factors.

4.8.2 Discussion on model building

The above discussion presents the realisation of connecting-tool mechanism in the supply chain and partially forms the answer to **RQ3**. To answer **RQ2**, a discussion is conducted here to summarise how the simulation model is built. Based on the macro-level description of OR-SCM framework mentioned in Section 3.4.4 (visualised in Figure 3.4), this chapter adds more details to each of the five components: Before-purchase behaviour, After-purchase behaviour, Online review system, Retailer activity, and Supplier activity. As the rest of the chapters will continue to discuss this framework, a unified description of OR-SCM framework will be presented in Chapter 7, together with the support reference listed in Appendix A2. In this chapter, the following texts will start to establish a *simplified* framework structure, with further details added in Chapters 5 and 6. Figure 4.8 summarises five components as well as the relevant activities considered in the model.

Before purchase

Estimated utility generation	1. Attributes based generation
	2. Distribution based generation
Review information interpretation and estimated utility update	1. Naïve interpretation (utility reflected in online reviews directly replaces estimated utility
	2. Weighted average interpretation
	3. Bayeisan update
Purchase decision	1. Updated estimated utility is greater than 0
	2. Updated estimated utility is greater than a threshold
Ordering behaviour	1. Order and wait to fulfill
	2. Order but leave if stock-out occurs

After purchase

Real utility generation	1. Distribution based generation
	2. Attributes based generation
Behaviour of rating	1. All customers rate
	2. Probabilistic rating decision
	3. Rating-utility based rating decision
Value of rating	1. Naïve rating (rating is equal to realised quality)
	2. Utility based rating
	3. Distribution based rating

Customers

Retailer

Inventory control	1. No inventory control
	2. Inventory control (e.g. order-up-to policy)
Competition	1. No competition
	2. Two or more retailers competing
	3. Competing itself(multi-channel)
Pricing	1. Price taker
	2. Optimal pricing

Supplier

Deficits of items	1. Equal quality for every item
	2. Occasional defective items
Sourcing	1. Single sourcing
	2. Daul sourcing
Pricing	1. Price taker
	2. Optimal pricing

Online review system

Format of rating	1. Real number (which can even be negative)
	2. Real number with only limited decimal points (1- or 2-digits) retained
Update procedures of rating	1. Calculating average value for all previously posted ratings
	2. Calulating average value for posted ratings in a specific time window
Quality of rating	1. All ratings are real
	2. Rating with real and fake (promotional) rating

Figure 4.8 OR-SCM framework for integrating online reviews in supply chain base model

4.8.2.1 Before-purchase behaviour

To model and simulate the Before-purchase behaviour, there are four elements considered in this chapter, namely estimated utility generation, estimated utility update based on review interpretation, purchase decision making, and order behaviours. First, this chapter uses an attribute-based way to generate customer utility, which follows the mainstream literature (e.g. Jiang and Guo, 2015; Kwark et al., 2014). However, the author also would like to mention some literature adopts a distribution-based way to model utility such as assuming it generated from a two-sided distribution (Bhole and Hanna, 2017). Compared with the distribution-based approach, the attribute-based approach explicitly considers the effect of customer heterogeneity and thus enables a deeper investigation on customer preference and product quality. Therefore, it is chosen in this chapter. After the estimated utility generation, customers will update their estimation based on online review information interpreted (Li and Hitt, 2010). In this chapter, a 'naïve interpretation' approach is adopted, meaning that customers will

assume the online review value is a direct reflection of real product quality (Hu et al., 2017; Li and Hitt, 2008). More sophisticated ways to model online review interpretation include weighted average methods (e.g. Jiang and Guo, 2015) and Bayesian update (e.g.Sahoo et al., 2018). Those methods introduce new factors into the experiments, such as the volume of posting, and it would be interesting to consider them in future research.

After updating the estimated utility under the interpretation of online reviews, customer purchase decisions need to be modelled. If customers are rational, they will purchase the product only if their expected utility is higher than their pre-determined threshold. Normally, this threshold is 0 as explained above. However, it shall be seen in Chapter 6 the threshold is not always 0 and other values can be adopted depending on the model assumption (as discussed in Anderson et al., 2009). Finally, after making decisions, customers will order the product. In this thesis, customers are assumed as impatient customers and will not wait if stock-out occurs. As argued above, although customers can be willing to wait, impatient customers are a more realistic assumption when modelling online shopping as the market can provide multiple alternatives for them to choose.

4.8.2.2 After-purchase behaviour

To simulate After-purchase behaviour, three elements will be modelled, namely real utility generation, behaviour of rating, and value of rating. First, after receiving the product, customers will generate their real evaluation (i.e. utility) of the product. Similar to what has been modelled in estimated utility generation, two types of modelling approaches, attribute-based and distribution-based generation can be adopted for modelling real utility generation. Consistent with the way used in estimated utility generation, attributed-based generation is adopted to generate real utility. After that, customers will decide their rating behaviour. The simplest way is to assume every customer will rate (e.g. Li and Hitt, 2008; Li et al., 2019a) while some papers model the rating behaviour as a probabilistic event where only some customers will post rates in the review system (e.g. Bhole and Hanna, 2017). As the probabilistic way to model rating behaviour is more realistic in practice (Ye et al., 2011), this thesis adopts it. In Chapter 6, the suitability of this approach will be better demonstrated, as the rating behaviour can be influenced by other factors (e.g. return decisions). Also, there exist some sophisticated modelling approaches for rating behaviour such as in Jiang and Guo (2015) or Hu et al. (2017)

where the rating behaviours are determined by the rating utility, which can be an interesting future direction to consider.

Finally, the value of rating needs to be generated. In this thesis, the value of rating is modelled in a naïve way in which the value is equal to the real quality experienced by the customers (Li and Hitt, 2008; Hu et al., 2017). However, based on different research focus, the value of rating can be assumed as a function of total real utility (e.g. Jiang and Guo, 2015) or generated from a pre-defined distribution (Bhole and Hanna, 2017).

4.8.2.3 Online review system

Three elements need to be modelled for online review systems, namely the format of rating, update procedure of rating, and quality of rating. First, the format of rating should be modelled so that the average value presented in the system can be calculated. The majority of research assumes the rating value is a continuous value within a pre-specified range such as from 0 to 1 as an abstract of the rating system in practice (see Li and Hitt, 2008 & 2010). As this approach is highly interpretable and easy to simulate, this thesis follows it. However, a few papers model the value as discrete values (such as {1,2,3,4,5} in Jiang and Guo (2015)), which complicates the model but makes it more like practical systems. Second, the update procedure in this thesis and the majority of the existing research is to calculate the mean value of all previously posted review ratings (except the research like Cai et al. (2018) which does not explicitly model an online review system). Therefore, this thesis follows this way and updates rating each period to the mean value. However, the author would like to mention that future research can examine other possible update procedures such that the mean value is calculated just based on the ratings posted within a specified time range. Finally, the quality of rating is modelled as all real, without considering online review manipulation/fraud and fake rating. However, as mentioned by Mayzlin (2006), reviews can be manipulated, and they are not always real. Therefore, review manipulation can be considered in future research, and one way to adapt the model in this chapter to model review manipulation is to assume the manipulated reviews equal to 1 as a favorable review.

4.8.2.4 Retailer behaviour

The retailer behaviour has three elements to consider in the model, namely inventory control, competition, and pricing. First, none of the previous studies (see Table 2.2 and Table 2.4) include inventory control in their models, meaning that every order can be fulfilled. This is unrealistic, endorsing the contribution of this thesis where order-up-to policy based on APIOBPCS framework is applied in the model. Second, previous studies highlight the competition in this field. Starting from the very first paper in this field by Kwark et al. (2014), many studies have addressed the connection between online reviews and market competition or self-competition (i.e. multi-channel retailing). Although this thesis does not include competition as an element for the model, it is a promising future direction (see Chapter 7). Finally, several papers modelled optimal pricing decisions of retailers under the influence of online reviews, but other papers assume the retailers as price taker (e.g. Minnema et al, 2016). This thesis adopts the latter approach to simplify the analysis and to focus more on the relationship between online review adoption and supply chain operations rather than pricing.

4.8.2.5 Supplier behaviour

Finally, the supplier behaviour needs to be modelled to complete the simulation model. As the research on this topic is still in its infancy, not so many variations are modelled on supplier behaviour. One component that concerns supplier behaviour is supplier pricing decision, and it is the same as that of retail behaviour where price taking or optimal pricing can be modelled. Another element as suggested in Figure 2.6 is the sourcing perspective where there can be a single supplier or two suppliers (i.e. dual sourcing). However, in the following chapters, two other elements, namely capacity of production (see Chapter 5) and deficits of items (see Chapter 7), will be considered. As these topics are not previously studied, they contribute to the existing literature.

4.9 Chapter summary

In this chapter, an uncapacitated forward supply chain based model is developed. Simulation experiments are conducted to examine the influence of online review adoption on supply chain profitability based on different customer quality estimation and lead time. All variables are

statistically significant factors for supply chain profit based on ANOVA results, but the customer quality estimation is the main moderator for online review adoption decision. Through this base model, this chapter builds the initial version of the modelling framework to integrate online reviews in supply chain modelling, paving the way for the following chapters. To sum up, this chapter forms answers for part of **RQ2** and **RQ3**.

CHAPTER 5

CAPACITATED MODEL

5.1 Chapter overview

This chapter aims to study how the adoption of online reviews can influence the performance of capacitated supply chain. Extending the base model in Chapter 4, this chapter also aims to answer part of **RQ2** and **RQ3**. A capacitated supply chain model considering the influence of online reviews is developed in this chapter, along with factorial simulation experiments to analyse it. Using supply chain profit as the performance measure, the results show that the influence of online review adoption on capacitated supply chain performance is complicated and significantly moderated by capacity constraint level, unit lost sales penalty and customer quality estimation.

5.2 Chapter background

Nowadays, supply chains are more constrained by their capacities as a consequence of demand surge and cost increase in production and information technologies (Angelus and Zhu, 2017). As different levels of capacity constraints can largely influence the supply chain performance (Cannella et al., 2008), examining the online review influence from a capacitated supply chain perspective can contribute to a thorough understanding of online reviews in supply chain management. Based on this motivation, this chapter extends the model in Chapter 4 to capacitated supply chain configuration and examines the interaction between online review adoption and variables related to supply chain capacity constraints.

Research on capacity constraints has been conducted for years, through which multiple facets of the influence of constraint on the supply chain have been examined. Many studies focus on the influence of constraints on supply chain profitability or cost efficiency. For example, Zhao et al. (2002) and Lau et al. (2008) studied the influence of capacity constraint on supply chain

cost efficiency. They defined a measure as 'capacity tightness' which is the ratio of capacity divided by demand. They found 'capacity tightness' has a moderating effect on the influence of other variables on supply chain performance. Freeman et al. (2018) studied the sourcing strategies of a manufacturer who has capacity constraints and unreliable supply. Using stochastic programming, they found that the different capacity constraint levels lead to the change of optimal sourcing strategy choices. Compared with the forward supply chain, Georgiadis et al. (2006) and Vlachos et al. (2007) studied the capacity constraint in remanufacturing and closed-loop supply chain. Given that capacity can be built and expanded by companies, these papers investigated the impact of alternative strategies for capacity planning under different situations by using simulation.

Although most papers tend to ignore the new product diffusion process, Shen et al. (2011) considered the new product diffusion problem when the product supply is constrained and analysed companies' optimal fulfillment and pricing policy. There is also research analysing the effect of capacity constraints on supply chain competition. For example, Qi et al. (2015) analysed how competitors in the same market should make investments in capacity to their shared supplier. In addition, the capacity constraint for the multi-echelon supply chain was also examined. For example, Angelus and Zhu (2017) studied the optimal policy under random demand as well as constraints on processing capacity in the multi-echelon supply chain under different situations.

Further, supply chain operational performance, such as customer service level or bullwhip level, is researched from the capacity constraint perspective. Cannella et al. (2008) investigated the effect of capacity constraints on supply chain operational performance measured by bullwhip effect and service level. They found an increase in capacity does not necessarily lead to a higher customer service level, but constrained capacity can reduce the bullwhip effect. Lin et al. (2014) explored the capacity constraints considering the customer baulking behaviour and they found that the interaction between constraints and baulking can have a significant impact on bullwhip effect. Ponte et al. (2017b) investigated the influence of capacity constraint on the bullwhip and fill rate of an order-up-to replenishment system with minimal-mean-square-error forecasting. They found there exists a threshold value, and capacity constraint can have a significant impact on supply chain performance when the constraint is lower than this threshold.

Dominguez et al. (2019) studied the constraints on the closed-loop supply chain where both the forward and reverse supply chain have capacity limits. They found constraints can relieve the bullwhip effects for both manufacturer and remanufacturer. Cannella et al. (2018) also explored the capacity constraints in the supply chain. Rather than assuming that the capacity constraint was a constant value, they modelled it as a dynamic and load-dependent constraint and found it can bring a negative influence on the supply chain system.

However, although the capacity constraint is an influential factor for the performance of the supply chain and the topic of the capacitated supply chain has been discussed from many perspectives, there is no research linking online reviews to the capacitated supply chain. Therefore, to fill this gap, **RQ3** is raised and studied below.

5.3 Model development

In this chapter, a capacitated E-commerce supply chain with online reviews is modelled. The model consists of two parts: demand generation and capacitated supply. A pictorial description for our model is presented in Figure 5.1 to compare when this supply chain adopts online reviews and when it does not adopt them.
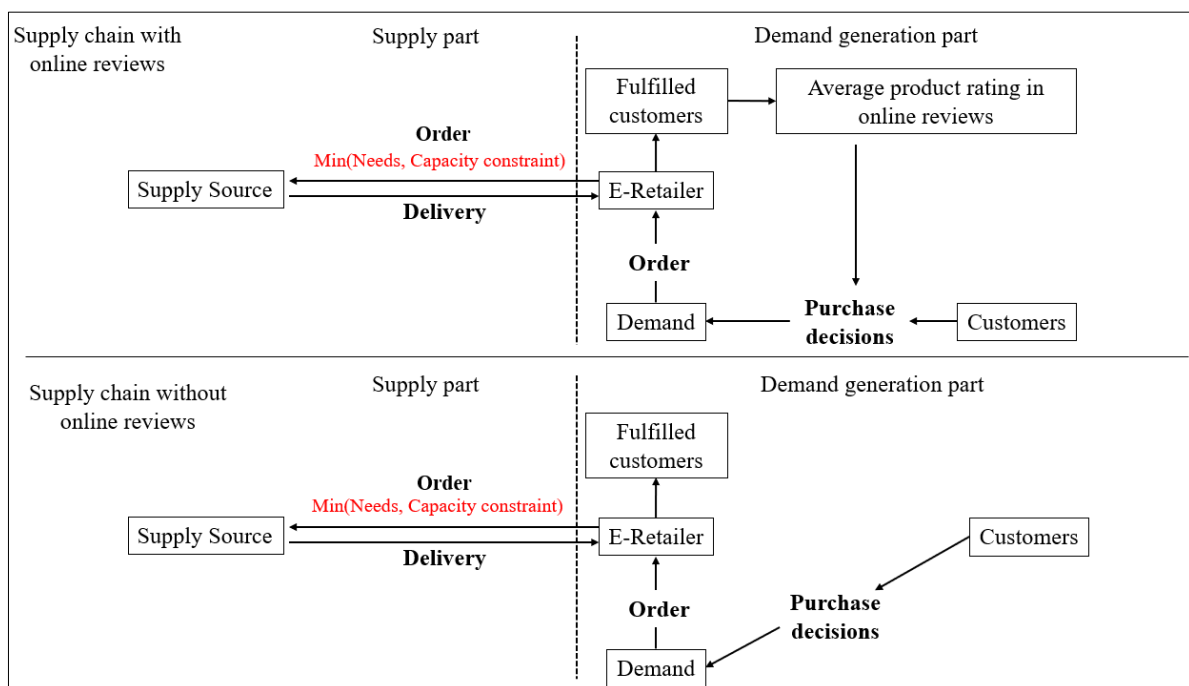
Figure 5.1 A capacitated supply chain model with/without online reviews

5.3.1 Model formulation

As this capacitated model is the extension of the base model in Chapter 4, except for the capacitated ordering rule, everything else remains unchanged. Therefore, the market side and supply side equations in Chapter 4 from equations (4.1) to (4.8) are identical. This implies the supply chain capacity will not affect the customer order decision process.

On the supply side, for ordering rules, equation (5.1) below is derived based on forecasting, inventory level, and work-in-process level. As the supply chain is capacitated, the order placed by the retailer cannot exceed capacity constraint (Ponte et al. 2017):

$$O_t = min(max((L + 1) * F_t - I_t - WIP_t, 0), CapCon) \qquad (5.1)$$

where $CapCon$ is the supply chain capacity constraint.

The value of price and different costs are still the same as Chapter 4, except the unit lost sale penalty level which is considered as an independent variable instead of a parameter, as it is important and directly linked to capacitated supply chain performance. Consistent with chapter 4, this chapter also adopts Metters' (1997) weekly analysis cost structure and assumes unit lost sale penalty has three levels, namely 0, 50% of production cost, and 100% of production cost (see Table 5.1 for all specific values). Therefore, the profit is still derived as follows:

$$Total\ Profit = Total\ Revenue - Total\ Holding\ Cost - Total\ Lost\ Sales\ Penalty$$

where each term is defined in Chapter 4.

5.3.2 Experimental design

Table 5.1 shows the values of parameters, independent variables, and the performance measure. The notations are consistent with Chapter 4. In this chapter, the main independent variable is adopting/not adopting online reviews in the capacitated supply chain. Apart from online review adoption, other independent variables are also considered. Consistent with Chapter 4, the first variable is q^e (i.e. quality estimation) as {over-estimation, under-estimation} which is equal to {0.7, 0.3}. Second, as this chapter concerns the supply chain capacity constraint, another independent variable examined is the capacity constraint ($CapCon$) with three levels, namely

{Tight, Medium, Loose} which are quantified as {10, 25, 40} respectively. The Tight constraint is defined as the capacity level lower than the mean demand in the under-estimation scenario while the Loose constraint is capacity level higher than the mean demand in the over-estimation scenario; the Medium constraint lies between these, which is equal to the mean demand when customers accurately estimate the quality. By doing so, all possible scenarios are considered in the simulation to achieve an exhaustive design. The terms 'Tight', 'Medium', and 'Loose' are used because using terms such as 'Low', 'Moderate' and 'High' can implicitly indicate that the capacity is independent of the mean demand. Finally, as the unit lost sales penalty will also determine the total lost sales penalty, it is also considered as a variable which has three levels, namely {Low, Moderate, High} and equals {0, 0.35, 0.7}. To measure performance, the profit of the supply chain is employed. Different from Chapter 4, the lead time is not considered as a variable but assumed as a fixed value, as the results in Chapter 4 show that lead time has little impact on moderating the influence of online reviews on supply chain performance. Also, assuming lead time as a fixed value is commonly seen in the previous modelling studies (e.g. Ponte et al., 2019; Dominguez et al, 2019; Potter and Lalwani, 2008).

Parameters	
q_{it}: real product quality	$U \sim (0,1)$
x_{it}: customer preference	$U \sim (0,1)$
p: product price	1
θ: forecasting smoothing parameters	0.2
L: lead time	4
N: customers each period (including all types of customers)	50
Unit cost of producing each product	0.7
Holding cost per product each period	0.0045
Probability of posting reviews	0.1
Independent variables	
Online review adoption	{Adopt; Not adopt}

Product quality estimation (q^e)	{0.3 (under-estimated); 0.7 (over-estimated)}
Capacity constraints ($CapCon$)	{10 (Tight), 25 (Medium), 40 (Loose)}
Unit lost sales penalty	{0 (Low), 0.35 (Moderate), 0.7(High)}
Performance measure	
Total Profit	

Table 5.1 Experiment parameters and variables for capacitated supply chain

This chapter again adopts a full factorial experimental approach based on the independent variables, where the total number of experiments is $2 * 2 * 3 * 3 = 36$. For each experiment, 20,000 periods are simulated with the first 3,000 as warm-up periods. 5 replications are conducted for each experiment. As noted in Section 4.4 in the last chapter, the simulation period is very long. Therefore, the criterion of Yang et al. (2011) and Cannella et al. (2018) mentioned in Chapter 4 can be easily met with five replications. The R codes are attached in Appendix A1, and the total running time for the program is approximately two working days. The simulation results are then analysed by using Analysis of Variance (ANOVA). The author conducted Shapiro-Wilk test and Levene's test to check the assumption of normality and homogeneity of variance, and no violation on the assumptions is found.

5.3.3 Simulation verification

The simulation is built in R programming language using RStudio. As this is an extension of Chapter 4, the same techniques used in Chapter 4 are adopted to verify the simulation program in this chapter. All verifications show that the proposed model has good accuracy.

5.4 Result analysis

The ANOVA results in Table 5.2 show that all independent variables have significant main and interaction effects on supply chain performance (profit) with a confidence level at 99%. As this paper seeks to study the influence of online reviews in capacitated supply chain

performance, analysis of main and interaction effects involving online review adoption variable will be the focus.

Variables	Df	Sum Sq	Mean Sq	F value	P value
OR	1	$1.37*10^{10}$	$1.37*10^{10}$	$3.76*10^5$	<0.01
LSP	2	$1.48*10^{11}$	$7.41*10^{10}$	$2.03*10^6$	<0.01
CC	2	$9.18*10^{11}$	$4.59*10^{11}$	$1.26*10^7$	<0.01
QE	1	$6.88*10^8$	$6.88*10^8$	$1.89*10^4$	<0.01
OR*LSP	2	$2.64*10^9$	$1.32*10^9$	$3.62*10^4$	<0.01
OR*CC	2	$2.68*10^{10}$	$1.34*10^{10}$	$3.68*10^5$	<0.01
LSP*CC	4	$1.82*10^{11}$	$4.54*10^{10}$	$1.24*10^6$	<0.01
OR*QE	1	$7.09*10^8$	$7.09*10^8$	$1.95*10^4$	<0.01
LSP*QE	2	$2.62*10^{10}$	$1.31*10^{10}$	$3.59*10^5$	<0.01
CC*QE	2	$9.11*10^{10}$	$4.56*10^{10}$	$1.25*10^6$	<0.01
OR*LSP*CC	4	$5.27*10^9$	$1.32*10^9$	$3.61*10^4$	<0.01
OR*LSP*QE	2	$2.63*10^{10}$	$1.31*10^{10}$	$3.60*10^5$	<0.01
OR*CC*QE	2	$9.16*10^{10}$	$4.58*10^{10}$	$1.26*10^6$	<0.01
LSP*CC*QE	4	$1.79*10^{10}$	$4.46*10^9$	$1.22*10^5$	<0.01
OR*LSP*CC*QE	4	$1.79*10^{10}$	$4.46*10^9$	$1.22*10^5$	<0.01
Residuals	144	$5.25*10^6$	$3.65*10^4$		

Remarks: OR: online review adoption decisions; LSP: unit lost sales penalty level; CC: capacity constraint; QE: quality estimation.

Table 5.2 ANOVA results

For the main effect of online review adoption on supply chain performance, Figure 5.2 reveals that, on average, adopting online reviews in a capacitated supply chain will lead to higher profit than not adopting them. Specifically, online review adoption leads to around 33% profit increase compared with no review scenario.
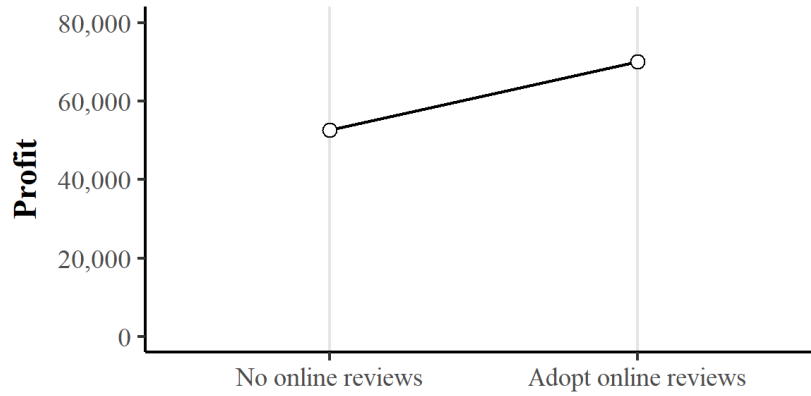
Figure 5.2 Main effect of online review adoption on supply chain profit

Figure 5.3 depicts the three first order interaction effects between online review adoption and quality estimation, unit lost sales penalty, and capacity constraint. For quality estimation interaction (Figure 5.3 (a)), online review adoption leads to higher profit in the supply chain, and the profit increase when quality is under-estimated is slightly smaller than the increase in the over-estimation scenario. For unit lost sales penalty interaction (Figure 5.3 (b)), higher profit can always be observed when adopting online reviews. The profit difference is larger when the unit lost sale penalty level is high, while it is less apparent when the penalty level is moderate and low. Finally, for capacity constraint interaction (Figure 5.3 (c)), the graph presents some evidence on the diverse influence of online review adoption. When the capacity constraint level is medium, a significant profit increase can be obtained by adopting reviews. However, when the capacity constraint is loose or tight, the influence of online reviews on profit nearly diminishes and almost no difference in profit is obtained from adopting them. This suggests complexity in the influence of online reviews on profit. In other words, although the first impressions of the main and first order effects seem to imply that online review adoption always makes the supply chain more profitable, in certain scenarios such influence is dubious. Therefore, to better reveal the mechanism of online review influence on the supply chain and to form the answer to **RQ3**, it is necessary to examine the second and third order interactions to capture the full picture of the influence of online review adoption.

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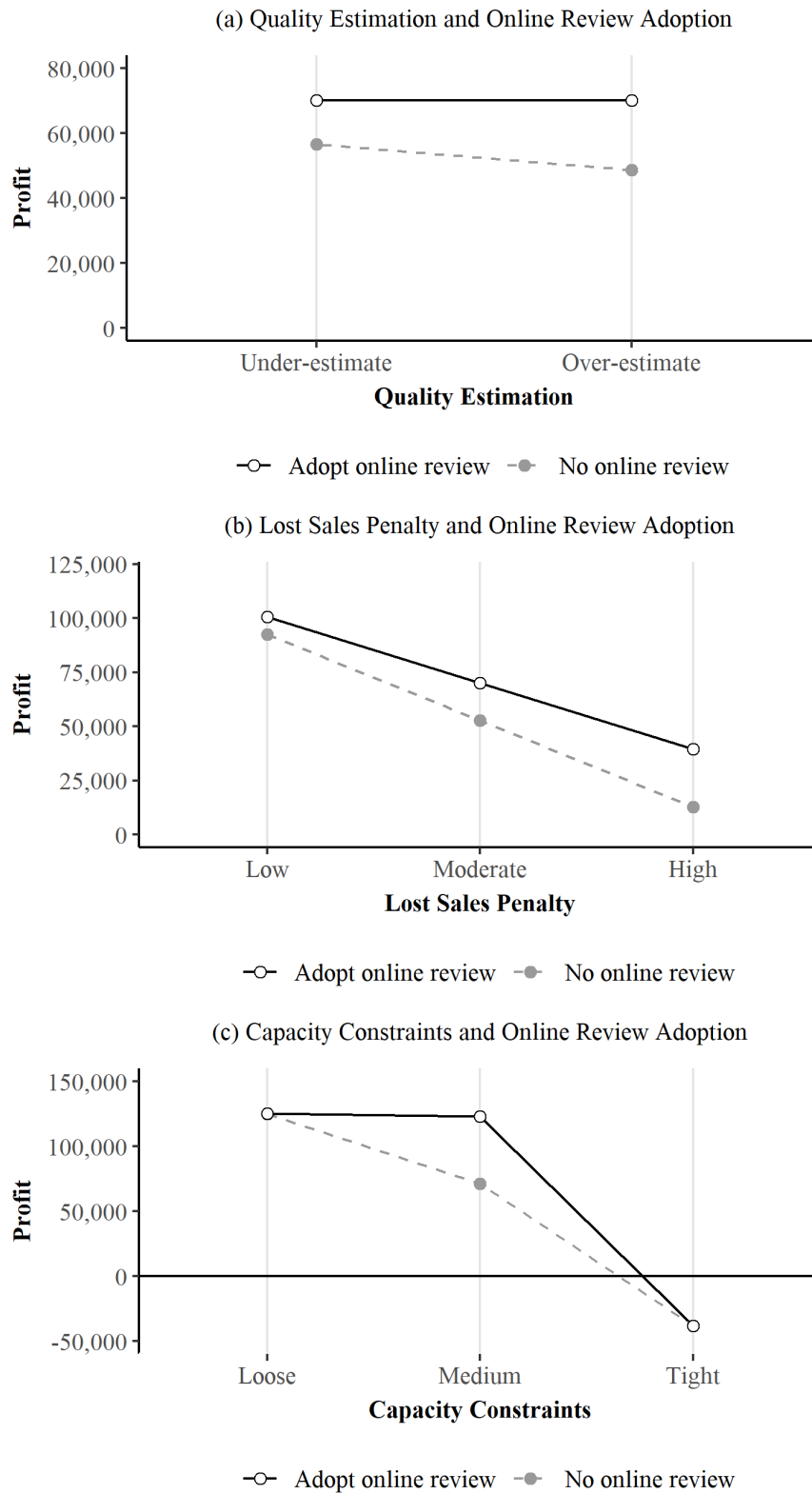
Figure 5.3 First order interaction effect on supply chain profit

Figure 5.4 depicts the second order effects, and the interaction effects between online review

adoption and unit lost sales penalty, as well as between online review adoption and capacity constraints are grouped by quality estimation. The second order interaction effect containing unit lost sale penalty (Figure 5.4 (a)) starts showing the diverse influence of online review adoption, and adopting online reviews does not always bring higher profit. If customers are over-estimating quality, more profit can be gained by adopting online reviews only when the unit lost sales penalty level is moderate or high. However, if quality under-estimation occurs, more profit can be obtained through adopting online reviews when the penalty level is low or moderate.
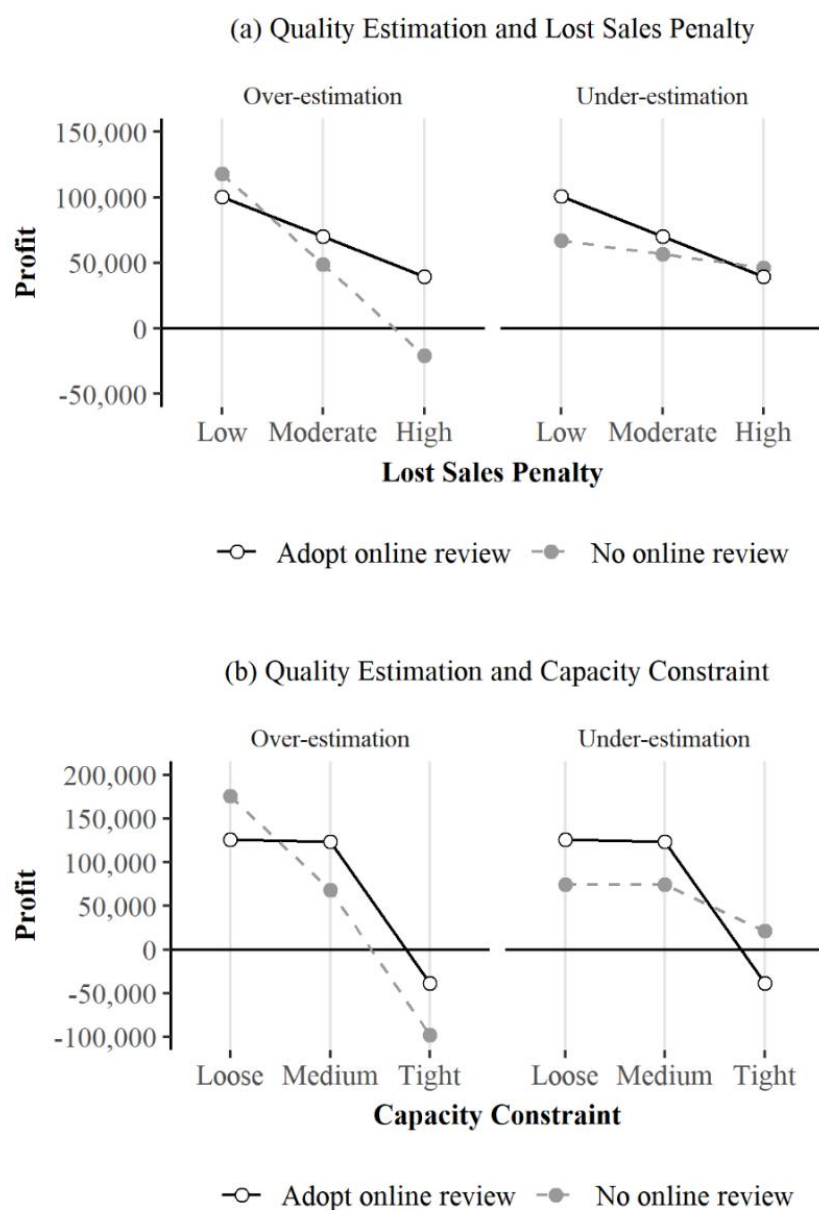
Figure 5.4 Second order interaction on supply chain profit

For the second order interaction involving capacity constraints (Figure 5.4 (b)), different influences of online reviews can also be observed. If quality is over-estimated, online review adoption leads to more profit or less loss when capacity constraints are medium or tight, but less profit when the constraints are loose. When quality under-estimation occurs, online reviews increase profit when the constraints are loose or medium, but decrease profit once the constraint level is tight.

Analysis of the second order interaction reveals the diversity of online review influence on supply chain profit, suggesting online reviews do not always lead to increased profit. In other words, the strategy of online review adoption needs to fit the diverse external environment factors of the company (i.e. different unit lost sale penalty levels, quality estimation, and capacity constraints).

Moreover, the third order interaction is analysed to further investigate such diverse influences. To better analyse and visualise the third order interaction effect, the profit between adopting online reviews and not adopting them is visualised in different scenarios in Figure 5.5. Here, it can be observed that the online review influence on profit gain is more diverse, which further confirms the results from the second order interaction analysis.

Quality Estimation

Over-estimation | Under-estimation
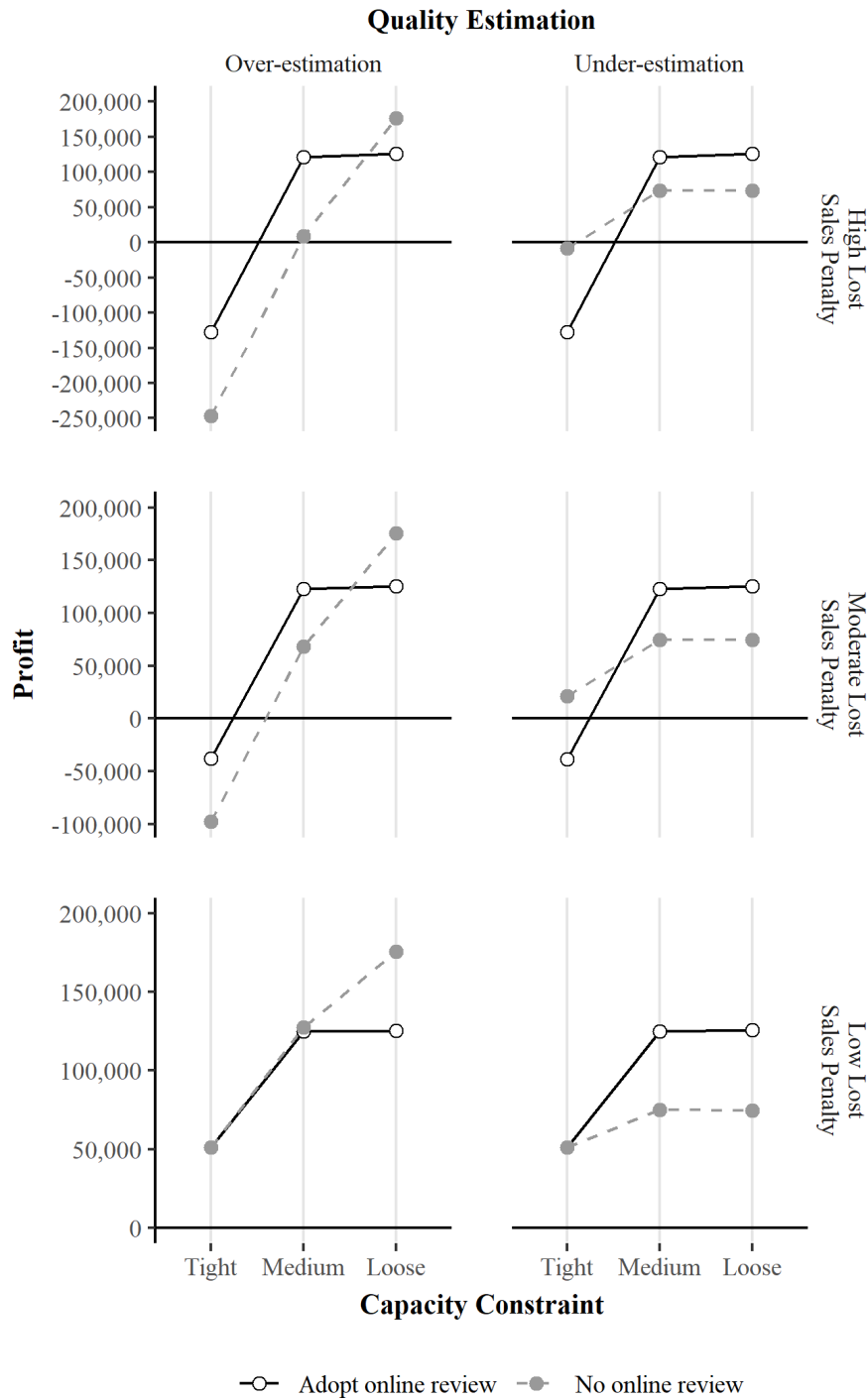
Figure 5.5 Third order interaction effect by profit

If quality is over-estimated, adopting online reviews will always lead to less profit when the capacity constraint level is loose. When the constraint level is medium, adopting online reviews makes little difference when the unit lost sales penalty level is low, but with a moderate or high unit lost sales penalty, more profit can be obtained if online reviews are adopted. When capacity

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constraint level is tight, online reviews are again beneficial in moderate or high unit lost sales penalty scenarios, albeit in reducing losses rather than increasing profit. On the other hand, when quality is under-estimated, if constraint level is loose or medium, adopting online reviews can lead to more profit for all penalty scenarios. For the case of tight constraint level in the under-estimation scenario, review adoption brings almost no profit difference when penalty level is low, but when penalty level is moderate or high, the profit loss can be observed if reviews are adopted, with the higher loss for high penalty level.

To identify the underlying causes of these quite diverse influences of online reviews on profit, it is better to analyse the revenue and different costs of the supply chain in different scenarios as well. In Figure 5.6 and Figure 5.7, the *value differences* related to revenue, different costs, and profit are presented, where the difference here is equal to the value of adopting online reviews minus the value without online reviews. The figures use 'Revenue', 'Holding cost', 'Lost sales', and 'Profit' to represent total revenue difference, total holding cost difference, total lost sale penalty different and total profit difference, respectively. For example, a revenue column in the following Figure 5.6 and 5.7 represents the revenue when online reviews are adopted minus the revenue without online reviews. In both figures, if a specific value is positive in a scenario, it reveals online review adoption increases this value in that scenario. Waterfall chart in Figure 5.6 and 5.7 show how the different cost elements contribute to the change in profit level. For clarity, the values for each change are also shown, as a negative change in holding costs or lost sales would have a positive impact on profit.

Note: Profit = Revenue - Holding Cost - Lost Sales.
Therefore, a negative change to Holding Cost or Lost Sales will lead to a positive change in profit (and vice versa)
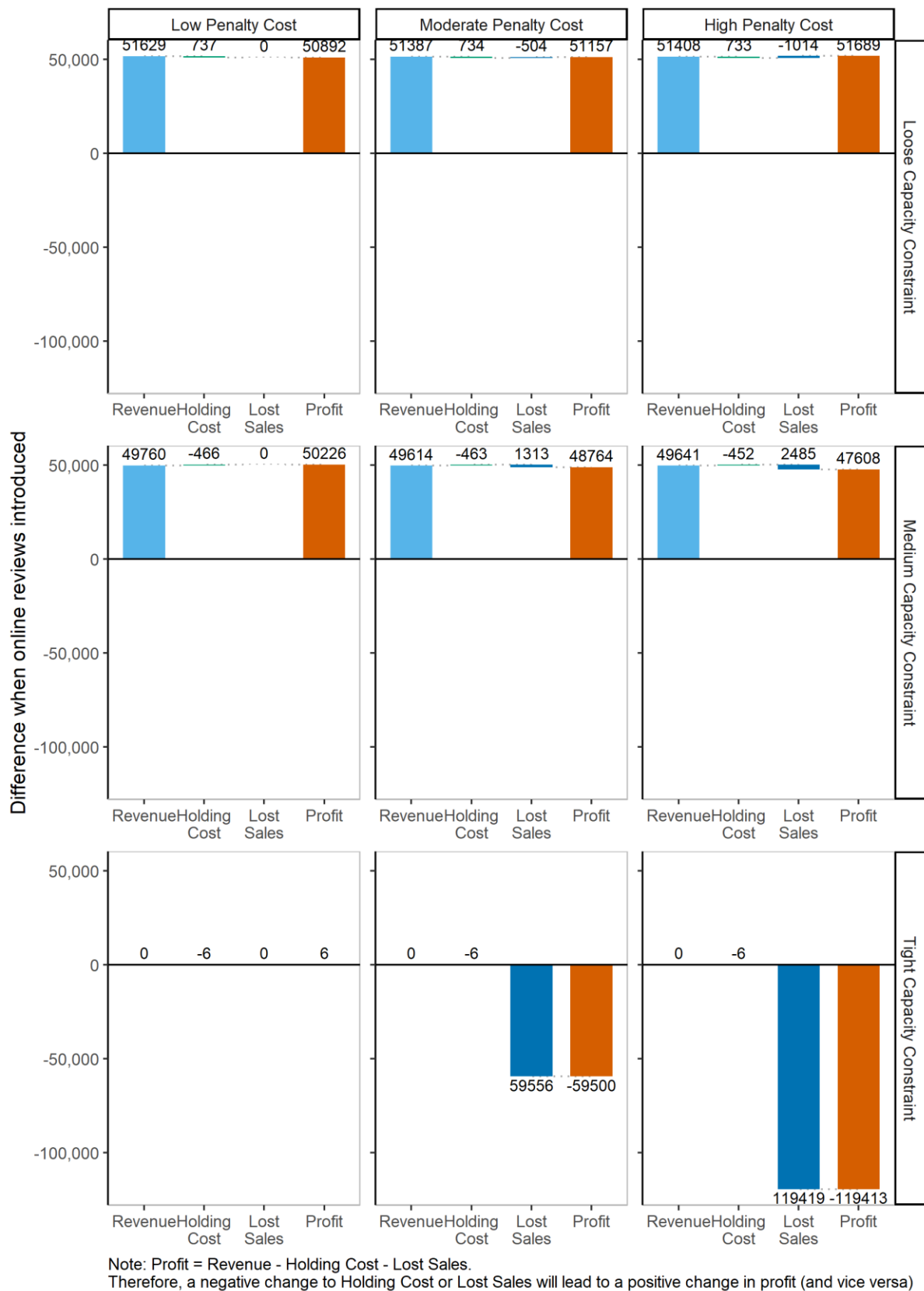
Figure 5.6 Waterfall chart showing changes to the value difference of profit, revenue, and cost when quality is under-estimated
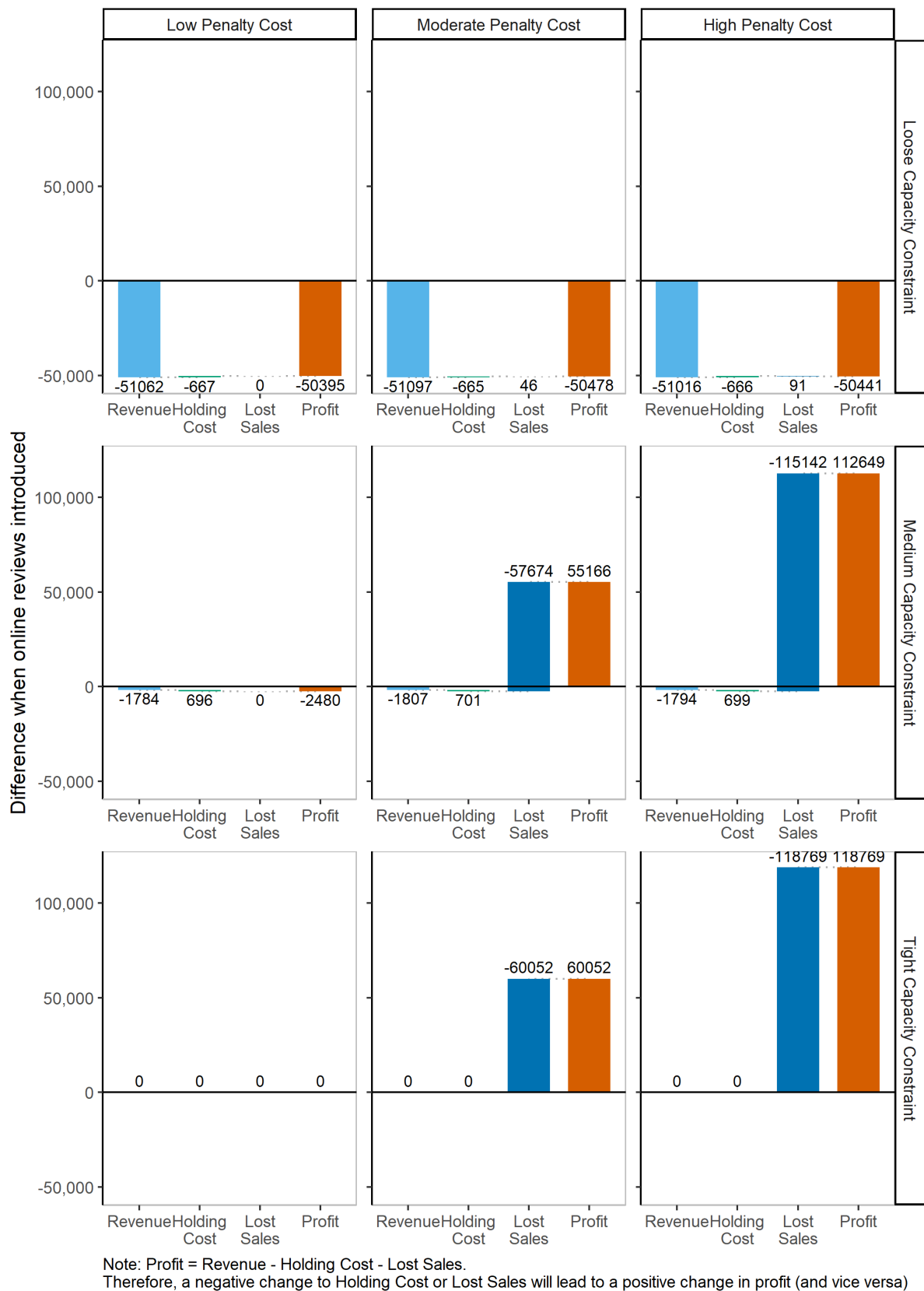
Figure 5.7 Waterfall chart showing changes to value difference of profit, revenue, and cost when quality is over-estimated

Across both Figure 5.6 and Figure 5.7, total holding cost difference columns are very small and therefore contribute little to the influence of online review adoption decisions. To verify this, a sensitivity analysis on the unit holding cost is conducted (Section 5.5). However, even the value of unit holding cost is amplified by 100%, the influence of total holding cost difference on the profit difference is still very small. Thus, it is not necessary to consider the impact of holding cost when deciding on the adoption of online reviews. In addition, the differences in total revenue and total lost sales penalty present roughly opposite effects on the profit difference, and these effects are essentially generated from the interaction between online review adoption and other independent variables.

To explain the relationship reflected in Figures 5.6 and 5.7 in detail, when quality is over-estimated, customers are falsely over-optimistic on product quality, and market demand will be high. Once online reviews are adopted, customer expectations on quality are corrected and market demand will decrease to be lower than the demand without online review. Comparing these two scenarios will generate the following insights. If the capacity constraint is loose, more products can be ordered and produced to fulfil customers. Therefore, in such a case, companies can benefit from adopting online reviews as they can have more market demand and generate more profit by fulfilling the increased demand. However, if the capacity constraint gets tighter, only limited products can be ordered to fulfil customers. This means, if companies still do not adopt online reviews, there will be higher market demand and some of them cannot be fulfilled. These unfulfilled customers lead to the occurrence of lost sales penalty. Therefore, companies now will prefer to adopt online reviews to decrease the sales penalty. These insights explain why adopting reviews lead to profit loss when the capacity constraint level is loose and the unit lost sales penalty is low, but lead to a significant profit increase when the capacity constraint level is tighter and the unit lost sales penalty is higher.

On the contrary, when quality is under-estimated, adopting online reviews corrects customer quality estimation bias and increases market demand. In this case, if the capacity constraint is loose enough, companies can benefit from adopting online reviews as more customer demand can be fulfilled without lost sales, eventually leading to more profit. Therefore, profit is higher for online review adoption when the capacity constraint is loose and quality is under-estimated. If capacity constraints are tighter and unit lost sales penalty higher, online review adoption

leads to more market demand, but companies cannot fulfil all of the increased demand, resulting in total lost sales penalty increase and eventually profit loss. In other words, companies now will benefit from not adopting online reviews.

5.5 Sensitivity analysis

In order to test the sensitivity of the simulation results to the simulation parameter, sensitivity analysis is conducted. As in this chapter, the unit lost sales penalty is an important variable and has been considered in the simulation experiments, the sensitivity analysis only considers varying the value of unit holding cost. Consistent with Chapter 4, sensitivity analysis is conducted by assuming the value of the unit holding cost as 0 and 0.009. Compared with results of the simulation where the unit holding cost is 0.0045, the sensitivity analysis reveals little difference, and the findings are qualitatively held. This indicates the robustness of the results of simulation experiments. As the sensitivity analysis table is long and the results are robust, the author shall omit the presentation of the table.

5.6 Discussion

Similar to Chapter 4, in this section, the results and the formation of simulations are discussed. The discussion on results is to partly form the answer to **RQ3**, while the discussion on simulation formulation extends the modelling framework proposed in Chapter 4 and contributes to the development of the answer for **RQ2**.

5.6.1 Discussion on simulation results

Based on the results of Section 5.4, Figure 5.8 visualises the causal relationships that connect online review adoption and its influence on supply chain profit. It can be seen although the influence of online reviews discussed in this chapter is a realisation of connecting-tool mechanism, the way online reviews influence the capacitated supply chain is not the same as the influence on uncapacitated supply chain in Chapter 4. The relative change between total revenue and total lost sales penalty determines whether the company can benefit from adopting online reviews. What should be noticed here is that inventory holding cost change caused by

online reviews are not considered, as Figure 5.6 and 5.7 together with the sensitivity analysis illustrate such change has little impact on the profit.
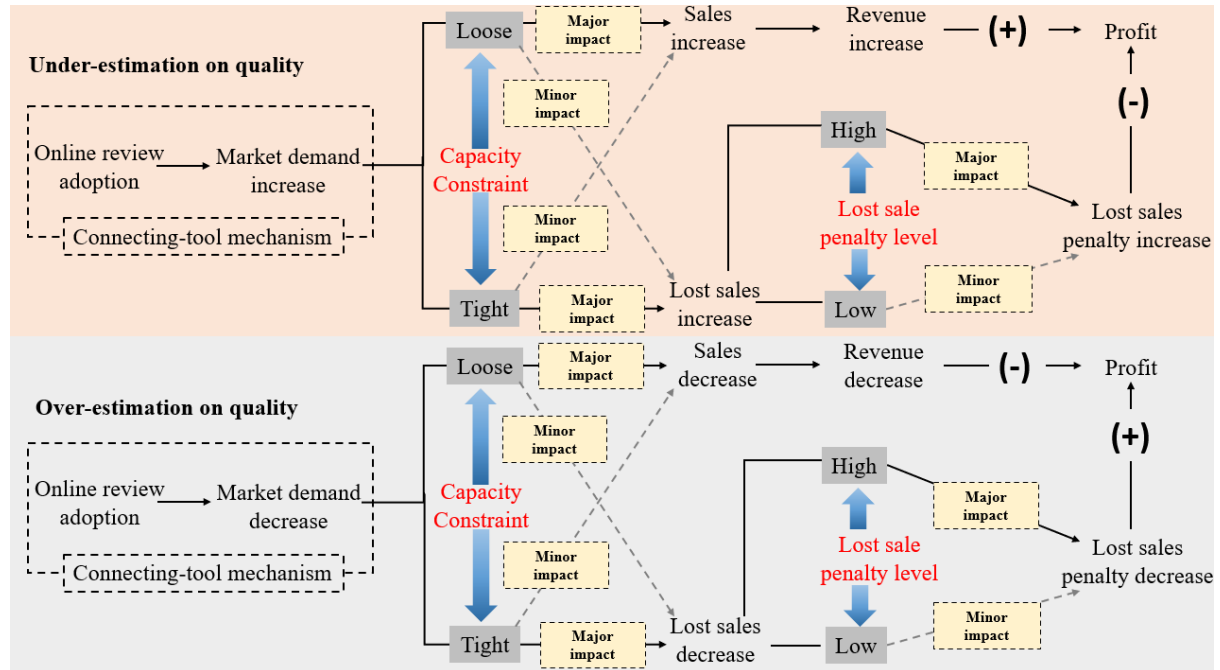
Figure 5.8 Influence of online reviews on capacitated supply chain

Specifically, when quality is under-estimated by customers, adopting online reviews can correct this under-estimation bias and increase the market demand. If the capacity constraint is loose, the increased demand can be fulfilled, which increases the sales and eventually the profit. However, if capacity constraint is very tight, the increased demand cannot be fully fulfilled, but lead to much more lost sales. Under such a case, if the unit lost sales penalty level is very low, the increased lost sales will not lead to a significant increase in total lost sale penalty. Once the unit lost sales penalty level is high, the dramatically increased lost sale penalty will then cause a severe profit loss. Put simply, the decision on online review adoption is determined by the ability of the supply chain to fulfil the increased demand.

When quality is over-estimated, adopting online reviews can correct customer over-estimation bias and lead to the market demand decrease. When the capacity constraint is tight, the lost sales of the company can be decreased, as the demand generated from over-estimation bias is higher than what can be fulfilled. If the unit lost sales penalty level is very high, such a decrease can relieve the company's profit loss on the total lost sales penalty, while it generates a small

impact if the unit lost sales penalty level is low. On the contrary, if the capacity constraint is loose, the fulfillment level is high even in the over-estimation scenario. Thus, under such circumstances, adopting online reviews does not relieve the lost sales but decreases sales, which eventually leads to a profit loss. Therefore, if customers over-estimate product quality, then the incentive is less to use online reviews unless capacity is tight because the reviews align demand and supply more effectively and reduce total lost sales penalty. To sum up, to develop the answer to **RQ3** the influence of online reviews in this chapter is summarised as follows:

> *In a capacitated forward supply chain, online review adoption significantly influences supply chain profitability by changing total supply chain revenue and total lost sales penalty, and such influence is moderated by quality estimation, capacity constraint, and unit lost sales penalty.*

The above findings also lead to the discovery of a counterintuitive and interesting phenomenon. Intuitively, companies will try to use different marketing approaches such as advertisements to make customers feel positive about their products. In effect, this encourages customers to increase their estimation of product quality. Online reviews can further contribute or mitigate this effect, depending upon whether they are positive or negative. However, the simulation results show that there are some circumstances where decreasing customer expectations of quality can increase profit levels due to changes in revenue and lost sales penalties.

To sum up, the influence of online review adoption highly depends on quality estimation, capacity constraint level, unit lost sales penalty level, and their interaction, illustrating that the adoption strategy should fit contextual factors from market and supply source. Previous literature indicates that to achieve high organisational performance, there should be a good fit between organisational characteristics to organisational and environmental contingencies (Donaldson, 2001). However, there is no universal best approach to fit all contingencies to attain a good performance (Teo and King, 1997). In information system research, the 'fit' focuses on the good adoption of information technology, and the adopted technology which fits organisational characteristics to different contingencies well can ensure the high performance of a company (Khazanchi, 2005; Morton and Hu, 2008). Consistent with previous literature, this chapter reveals that adopting/not adopting online reviews should also fit a company's specific contingencies (i.e. quality estimation, capacity constraint level, and unit

lost sales penalty level). It also implies the value of online reviews should not be evaluated by their impacts on the demand or customer purchase intention alone, but be measured from the whole supply chain system's profitability.

5.6.2 Discussion on model building

In this chapter, the model extends Chapter 4 and includes the capacity constraints on the supply side. Figure 5.9 updates the OR-SCM framework in Chapter 4 to the capacitated supply chain configuration.

Before purchase	
Estimated utility generation	1. Attributes based generation
	2. Distribution based generation
Review information interpretation and estimated utility update	1. Naïve interpretation (utility reflected in online reviews directly replaces estimated utility
	2. Weighted average interpretation
	3. Bayeisan update
Purchase decision	1. Updated estimated utility is greater than 0
	2. Updated estimated utility is greater than a threshold
Ordering behaviour	1. Order and wait to fulfill
	2. Order but leave if stock-out occurs

After purchase	
Real utility generation	1. Distribution based generation
	2. Attributes based generation
Behaviour of rating	1. All customers rate
	2. Probabilistic rating decision
	3. Rating-utility based rating decision
Value of rating	1. Naïve rating (rating is equal to realised quality)
	2. Utility based rating
	3. Distribution based rating

Retailer	
Inventory control	1. No inventory control
	2. Inventory control (e.g. order-up-to policy)
Competition	1. No competition
	2. Two or more retailers competing
	3. Competiting itself(multi-channel)
Pricing	1. Price taker
	2. Optimal pricing

Supplier	
Capacity of production	1. Unlimited
	2. Capacitated
Deficits of items	1. Equal quality for every item
	2. Occasional defective items
Sourcing	1. Single sourcing
	2. Daul sourcing
Pricing	1. Price taker
	2. Optimal pricing

Customers

Online review system	
Format of rating	1. Real number (which can even be negative)
	2. Real number with only limited decimal points (1- or 2-digits) retained
Update procedures of rating	1. Calculating average value for all previously posted ratings
	2. Calulating average value for posted ratings in a specific time window
Quality of rating	1. All ratings are real
	2. Rating with real and fake (promotional) rating

Figure 5.9 OR-SCM framework for integrating online reviews in capacitated supply chain

First, as the extension is made in the supply chain, customer side structure will not be influenced. Therefore, customer Before-purchase behaviour will remain the same, and they generate their estimated utility for the product under the influence of online review information and make purchase decisions accordingly. Meanwhile, the After-purchase behaviour is also

unchanged, and customers will generate real utility of the product and pose online reviews following the rules the same as Chapter 4. In addition, for the online review system, its rule for receiving and updating the rating information works the same where the average rating presented in the system is the mean value of all posted ratings.

The difference comes from the supply side. Compared with the model in Chapter 4 where the supplier is assumed to have infinite capacity, the supplier in this chapter is modelled as a capacitated supplier. The change in the capacity assumption leads to the adjustment of the retailer ordering rule, and only the order quantity no more than the capacity constraint can be placed to the supplier for production (Cannella et al., 2008; Ponte et al., 2017). As this change is observed becoming a significant influencer of online review adoption decisions, it is worth adding to the framework.

5.7 Chapter summary

This chapter examines the influence of online reviews on capacitated supply chain performance (profit) by extending the base model in Chapter 4 to a capacitated supply chain configuration. The results reveal that overall, online reviews can increase the profitability of capacitated supply chain, but compared with the influence of online reviews discussed in Chapter 4, the influence in this chapter significantly interacts with other factors including customer quality estimation, capacity constraints, and unit lost sale penalty level. The findings of this chapter contribute to the answer to **RQ3**, and the modelling methods used in this chapter enrich the OR-SCM framework and form the answer of **RQ2**.

CHAPTER 6

CLOSED-LOOP MODEL

6.1 Chapter overview

This chapter extends the base model and studies the influence of online reviews on closed-loop supply chain performance. This chapter addresses part of **RQ2** and **RQ3**. The supply chain profitability is adopted as the performance measure, and the simulation considers the influence on profitability from three independent variables namely online review adoption, customer estimation on product quality, and unit reverse supply chain cost, with their main effects and interactions examined. Further, sensitivity analysis on two parameters, namely customer return cost and probability of review posting of customers who keep the product, is conducted. As this chapter is an extension of Chapter 4, it is also a study of the customer-customer information sharing function (Section 2.3.2) and a realisation of connecting-tool mechanism (Section 2.3.3). The model assumes the supply chain structure as a supplier and a retailer with customer product return, consistent with the structure F in Figure 2.6.

6.2 Chapter background

The increased awareness of the importance of sustainability leads companies to pay more attention to closed-loop supply chain practices. A good design of the closed-loop supply chain can enhance the performance of cost-saving and profitability of companies, as well as realise their corporate responsibility in the environment and society (Govindan and Soleimani, 2017). This is especially true for the current days as the rapid development of new production technologies and the change of customer purchase behaviours largely shorten the product life cycle, which leads to much more product returns and wastes than before (Shaharudin et al., 2017). Also, the prosperity of E-commerce and online retailing contribute to the enormously increased transactions, which further stimulates the increasing volume of the product return. A recent survey shows that in the United States, the cost on product return delivery reached $350 billion in 2017 and estimated to be $550 billion in 2020 (Mazareanu, 2020).

In previous research, there are many topics on closed-loop supply chain investigated, ranging from closed-loop supply chain structure design (Dominguez et al., 2020), replenishment policy development (Tang and Naim, 2004), capacity building (Georgiadis et al., 2006), among others. However, the systematic literature review in Chapter 2 finds no study explicitly examined the influence of online reviews in the closed-loop supply chain (although several studies link online reviews to product return). The development of E-commerce makes online reviews frequently used, and customers are getting used to seeking product information from them before purchase. The signals delivered from reviews enable customers to infer whether the product can fit their expectations and preference, which then support their purchase decisions (Li and Hitt, 2010). Some studies explored the online review influence on product return, such as how review volume and valence can influence customer return decisions (Sahoo et al., 2018; Minnema et al., 2016; Walsh and Möhring, 2017), but none of them touched how such influence will determine the performance of overall closed-loop supply chain. From a company's perspective, it is undoubtedly true that knowing how to utilise online reviews to improve the closed-loop supply chain performance will be more important than merely knowing how online reviews can influence customer return behaviour. The gap here therefore motivates the raise of **RQ3**, and the author believes closing this gap can shed light on the use of online reviews to enhance closed-loop supply chain performance and inform companies of better decisions.

6.3 Model formulation

In this paper, a simulation model is used to examine the influence of online review adoption on supply chain performance. A graphical demonstration of the closed-loop supply chain process is in Figure 6.1 where two scenarios, namely adopting and not adopting online reviews are compared.
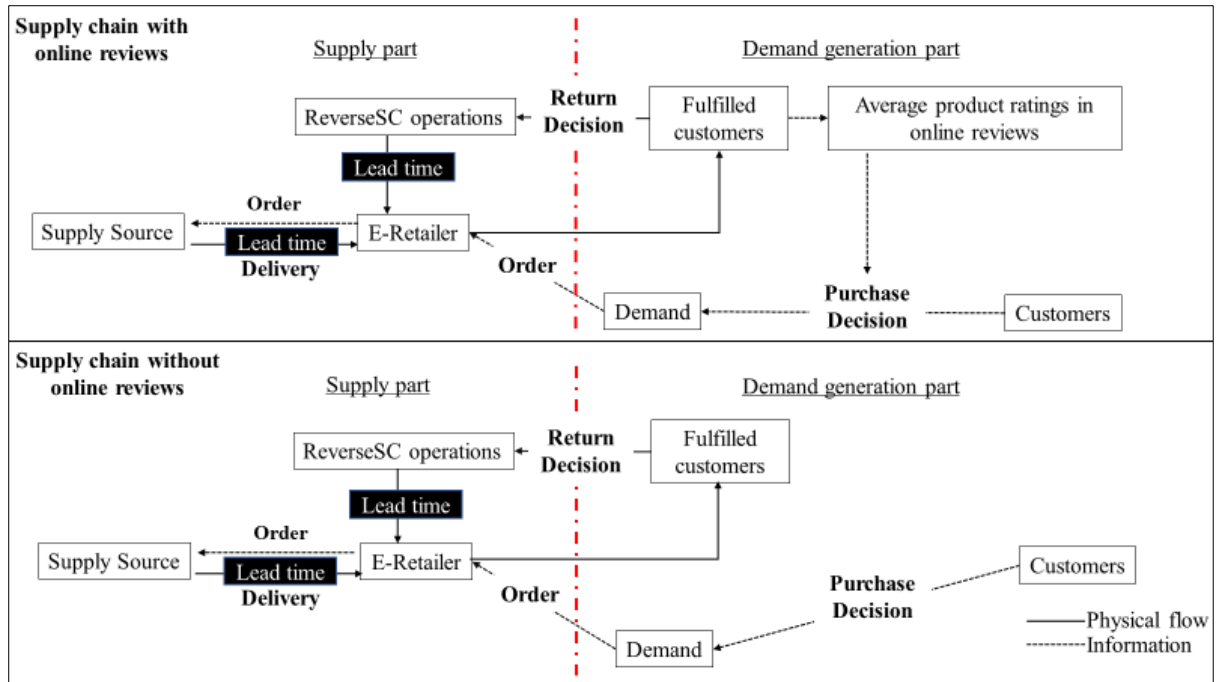
Figure 6.1 Closed-loop supply chain with/without online review influence

6.3.1 Demand generation

The formulation begins from customer demand generation, and agent-based modelling is adopted. A complete version of the decision rules for agents is presented in Figure 6.2. The equations and notations in Figure 6.2 will be introduced in detail subsequently.
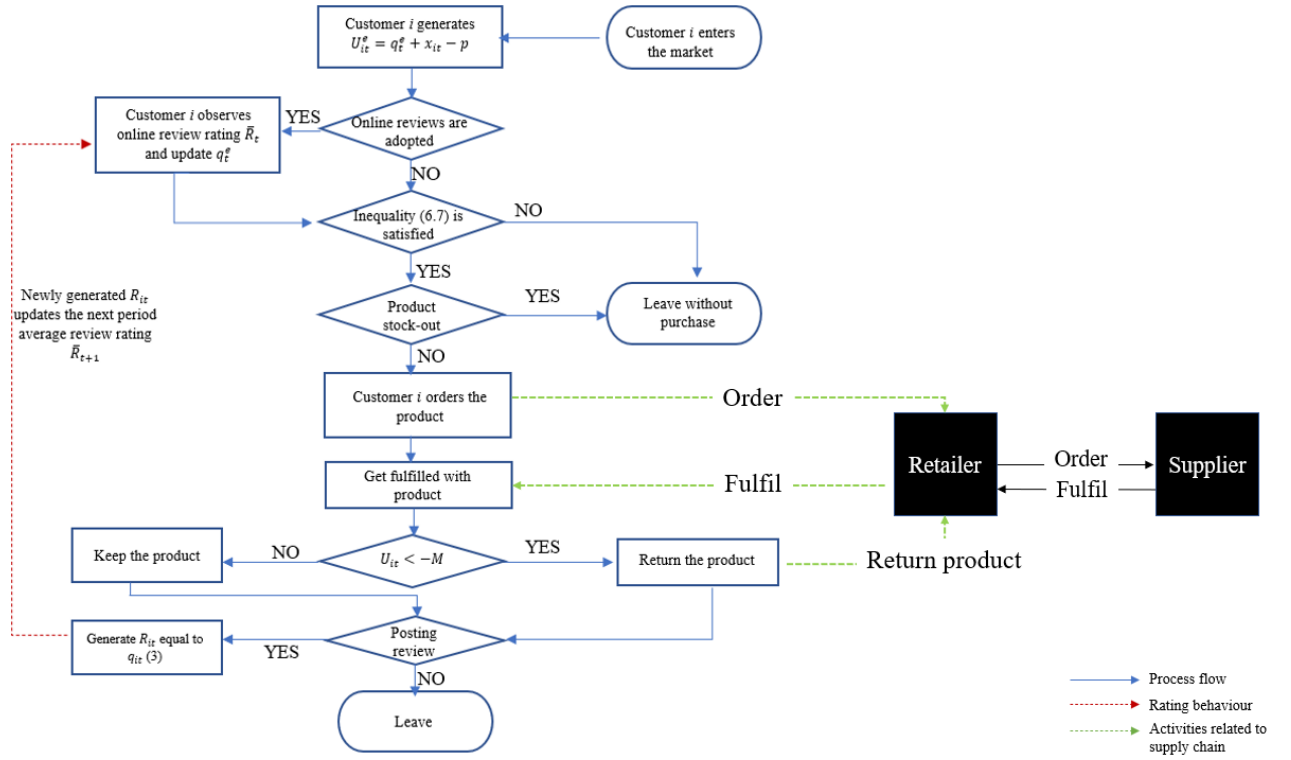
Figure 6.2 The flowchart for agent-based modelling in the closed-loop supply chain model

Here, each agent is assumed as a customer, and customer is coded as i in period t to indicate the attributes of ith customer entering the market in period t. As this chapter is the extension of Chapter 4, it still starts from modelling customer attributes and associated utility. According to Li and Hitt (2008), Hu et al. (2017) and Papanastasiou and Savva (2017), the utility of customer i in period t, U_{it}, of consuming a product after purchasing consists of three parts: quality of the product q_{it}, customer preference on the product x_{it} and product price p, and:

$$U_{it} = q_{it} + x_{it} - p \qquad (6.1)$$

Consistent with Hu et al. (2017), this chapter assumes $q_{it} \sim N(q_\mu, \sigma_\mu^2)$, where the q_μ is the true mean product quality which is unobservable, while σ_μ reflects the difference of quality perception for each customer after purchase and is common knowledge (Papanastasiou and Savva, 2017). It should be noticed that in this chapter, the quality is assumed as a normal distribution, which is slightly different from the previous two chapters where a uniform distributed quality is assumed. The reason for such a change is to enable this chapter to include the return decision in the agent-based model. It should be noted that both uniform and normal distributions are very similar and are widely used in previous research (for example Kuksov

and Xie (2010) assumes uniform distribution while Hu et al. (2017) assumes normal distribution). For preference x_{it}, it still is assumed uniformly distributed between 0 to 1 (i.e. $x_{it} \sim U(0,1)$), and the realisation of x_{it} is a customer's private knowledge and known to each customer before purchase (Li and Hitt, 2008). Also, no correlation between x_{it} and q_{it} is assumed to be consistent with the previous chapters.

As the q_μ is unknown before purchase, customers should estimate it when making ordering decisions. No matter online reviews are available or not, customers will form an estimation on it so that they can make their purchase decisions accordingly. Based on Li and Hitt (2008 & 2010) and Hu (2017), when there is no online review available, customers will have an exogenously given and homogenously time-invariant estimation on the true mean quality, and this chapter notates this estimation as q_μ^e. Therefore, for customers, their estimated quality before purchase is $q_t^e \sim N(q_\mu^e, \sigma_\mu^2)$ if online reviews are not accessible. As customers can have a biased estimation on true mean quality (Shapiro, 1983; Li and Hitt, 2008), this chapter considers q_μ^e not necessarily equal to q_μ. It should be noted that there is no subscript 'i' in q_t^e, meaning that the estimated quality for each customer is an identical distribution rather than a specific realisation of it. When in period t, there are online reviews available and the average rating showing in the system is $\bar{R}_t$. Consistent with previous chapters, the customers will use $\bar{R}_t$ as a representative of true mean quality and update their estimation q_μ^e as $\bar{R}_t$ (Li and Hitt 2008). In other words,

$$q_t^e \sim \begin{cases} N(q_\mu^e, \sigma_\mu^2), & \bar{R}_t \text{ is not available} \\ N(\bar{R}_t, \sigma_\mu^2), & \bar{R}_t \text{ is available} \end{cases} \tag{6.2}$$

This chapter denotes the cumulative density function (CDF) of q_t^e as $F(q_t^e)$ and the probability density function (PDF) of q_t^e is $f(q_t^e)$. Before purchase, as customers have no information about the true mean quality, they will form their estimated utility, U_{it}^e, of buying a product based on their estimation and use it to make purchase decision, and thus

$$U_{it}^e = q_t^e + x_{it} - p \tag{6.3}$$

Consistent with Li and Hitt (2008, 2010) and Hu (2017), such a way of modelling is essentially a simplification of Papanastasiou and Savva (2017), as the uncertainty of the estimation is not considered, and the customers are assumed completely certain about their estimation. A more sophisticated method, proposed by Papanastasiou and Savva (2017), is to use Bayesian update

to model the influence of online reviews on estimation. However, as argued by Li and Hitt (2010), the simplification can also capture the feature of the online review influence on customer decisions well. Therefore, the way adopted in this thesis is proper for the research question as it is not only able to be used to answer the research questions well but also can significantly save the running time of the simulation program.

To derive the purchase decision of customers, this chapter models the customers as forward-looking based on Sahoo et al. (2018) and Anderson et al. (2009). First, the utility of the best alternative of the product is assumed as 0. Also, if a customer hopes to return the product, the return process will generate a return cost equal to M where $M > 0$ can measure the money related to the return delivery process or the time and effort spent by customers on product return (Anderson et al., 2009). The M is assumed to be known to every customer before purchase, and it will influence customer purchase as well as return decision. After receiving the product, a customer will decide to keep the product if $U_{it} > -M$, or to return the product otherwise. If customer i keeps the product, they will get a utility of U_{it}. If they return the product, nothing will be obtained but with M spent, meaning that the utility of returning a product is $-M$. However, as customers can only use U_{it}^e to estimate U_{it}, they will make purchase decisions by considering U_{it}^e. Specifically, after considering the M and the related utility, a customer i in period t will buy the product only when

$$E[U_{it}^e|U_{it}^e > -M]\Pr(U_{it}^e > -M) + (-M)\Pr(U_{it}^e < -M) > 0 \qquad (6.4)$$

To better demonstrate how inequality (6.4) links to the real utility U_{it}, Table 6.1 compares different scenarios. What should be specifically noted is the second row of the table where even the $U_{it} < 0$, a rational customer will choose to keep but not return the product if $U_{it} \geq -M$. In practice, this means even though customers are unsatisfied, they will think the hassle and cost of returning the undesirable product are unacceptable and it is preferable to just keep it.

Before purchase	Order decisions	After purchase	Return decisions
Inequality (6.4) satisfied	Order product online	$U_{it} \geq 0$	Keep
Inequality (6.4) satisfied	Order product online	$-M \leq U_{it} < 0$	Keep
Inequality (6.4) satisfied	Order product online	$U_{it} < -M$	Return
Inequality (6.4) not satisfied	Leave without ordering	N/A	N/A

Table 6.1 Purchase and return decisions

Recalling that x_{it} is known to each customer before purchase, (6.4) can be formulated as

$$E[q_t^e + x_{it} - p | q_t^e + x_{it} - p > -M](1 - F(p - x_{it} - M)) + (-M)F(p - x_{it} - M) > 0 \quad (6.5)$$

Expanding left-hand side of (6.5), the purchase criterion for a specific customer i in t is

$$(1 - F(p - x_{it} - M)) \int_{p-x_{it}-M}^{+\infty} (q_t^e + x_{it} - p)f(q_t^e)dq_t^e + F(p - x_{it} - M)(-M) > 0 \quad (6.6)$$

As the first component of the left-hand side of (6.6) has a partial expectation of normal distribution, it is not easy to directly code in the simulation package. Therefore, to ensure the coding process is correct and to avoid the system errors, (6.4) to (6.6) are cross-checked with the following reformulation as

$$(1 - F(p - x_{it} - M)) \int_{p-x_{it}-M}^{+\infty} (q_t^e + x_{it} - p)f(q_t^e)dq_t^e + F(p - x_{it} - M)(-M)$$

$$= (1 - F(p - x_{it} - M))[\int_{p-x_{it}-M}^{+\infty} q_t^e f(q_t^e)dq_t^e + \int_{p-x_{it}-M}^{+\infty} (x_{it} - p)f(q_t^e)dq_t^e] + F(p - x_{it} - M)(-M)$$

$$= (1 - F(p - x_{it} - M))[\int_{p-x_{it}-M}^{+\infty} q_t^e f(q_t^e)dq_t^e + (x_{it} - p)(1 - F(p - x_{it} - M))] + F(p - x_{it} - M)(-M)$$

$$= (1 - F(p - x_{it} - M))[\hat{q} - \int_{-\infty}^{p-x_{it}-M} q_t^e f(q_t^e)dq_t^e + (x_{it} - p)(1 - F(p - x_{it} - M))] + F(p - x_{it} - M)(-M)$$

$$= (1 - F(p - x_{it} - M))\left[\hat{q} - \left(\hat{q}\Phi\left(\frac{p-x_{it}-M-\hat{q}}{\sigma_\mu}\right) - \sigma_\mu\phi\left(\frac{p-x_{it}-M-\hat{q}}{\sigma_\mu}\right)\right) + (x_{it} - p)(1 - F(p - x_{it} - M))\right] + F(p - x_{it} -$$

$$M)(-M) > 0 \quad (6.7)$$

(see Winkler et al., 1972)

where $\hat{q} = \begin{cases} q_\mu^e, \bar{R}_t \text{ is not available} \\ \bar{R}_t, \quad \bar{R}_t \text{ is available} \end{cases}$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are the CDF and PDF of the standard

normal distribution with its mean value equal to 0 and variance to 1, respectively. $F(\cdot)$ and $f(\cdot)$ are the CDF and PDF of customer estimated quality which are defined above. Now, every

component of (6.7) can be directly computed as only normal distribution's CDF and PDF are needed. As (6.7) is equivalent to (6.4), the author therefore used inequality (6.7) to cross-check his codes for (6.4) to ensure the codes are programmed correctly. The (6.4) to (6.7) reflect a different type of purchase decision making compared with that in Chapters 4 and 5. It can be observed that in Chapters 4 and 5, the purchase decisions are linear on the customer side, with the nonlinearities only existing supply side. However, because of the consideration of customer return behaviour in the closed-loop model, even the customer side decision making becomes nonlinear and heterogeneous. Such a difference turns to the results more analytically intractable (see Sahoo et al. (2018)), which again suggests the suitability of agent-based modelling in this study.

If customer i in period t satisfied inequality (6.4) to (6.7), they will purchase the product, otherwise leave the system. After purchasing, if customers can get fulfilled when the product is not stock-out, they will generate U_{it} after purchase and decide whether they keep the product based on the above criteria depicted in Table 6.1. If such a customer cannot get fulfilled because of the stock-out, this chapter assumes they will leave (Cannella et al., 2019). For those customers leaving without purchasing or without fulfilling, they cannot experience the U_{it}. For the computational purpose, their U_{it} is set as 0.

Meanwhile, if the online review system is adopted by the supply chain, the customers who get fulfilled will also need to decide if posting a rating for the product. Based on Li and Hitt (2008), if customers are willing to post a rating, they will post their rating, R_{it}, equal to q_{it}. Based on all previously posted ratings, the $\bar{R}_t$ can be calculated by the average of all R_{it} spanning from the second period to the present. In addition, Sahoo et al. (2018) observed empirically that the customers who return a product are more likely to post a rating than customers keeping the product. This illustrates the quality information reflecting from $\bar{R}_t$ can be slightly biased depending on the relative probability of different customers in review posting. In Sahoo et al.'s (2018) paper, specifically, customers who return products are 35% more likely to rate products than customers who keep the products. In other words, their observation suggests that if the probability of posting for customers who return the product is 100%, the probability of rating for customers keeping the product is around 74% (i.e. $\frac{100\%}{1.35}$). Therefore, this thesis uses 100% and 74% as the probabilities of posting reviews for customers returning and customers keeping

products in the simulation experiments (see experiment design in Section 6.4), respectively. Also, a sensitivity analysis on different rating probability is conducted to check the effect of rating probability on the results (see Section 6.7).

6.3.2 Supply chain modelling

After modelling the customer side, the supply side model is developed based on system dynamics and the APIOBPCS framework is followed. Different from the previous Chapters 4 and 5, to allow product return this chapter adapts the system from Tang and Naim (2004) and Dominguez et al. (2019). First, this chapter still assumes in each period t there are N customers coming to the online E-commerce website, and N is set as 50. Based on (6.4) to (6.7), the demand in period t, D_t, is the number of these customers who satisfied the inequality.

The demand will be fulfilled by inventory on-hand in the last period, I_{t-1}, newly arrived product ordered L period ago, denoted as O_{t-L}, as well as returned products which were returned L_r periods ago, denoted as r_{t-L_r}. Here L is the SC manufacturing lead time and L_r the reverse supply chain lead time. Here, the time spent on the reverse supply chain can be used on returned product collection, product repackaging, or refurbishment. Therefore, the fulfilled demand D_t^* will be the

$$D_t^* = min\big(O_{t-L} + I_{t-1} + r_{t-L_r}, D_t\big) \tag{6.8}$$

with unfulfilled customers leaving (Cannella et al., 2019), and thus no backlog is permitted. Consistent with Dominguez et al. (2019) and Teunter and Vlachos (2002), this chapter assumes the reverse supply chain lead time L_r is equal to the forward supply chain production lead time L. Therefore, according to Tang and Naim (2004) and Dominguez et al. (2019), the system lead time for the whole closed-loop supply chain system is still L.

As the fulfilled customers may not satisfy with the product, they need to return it. Under the criteria described above, the returned product volume in period t, r_t is

$$r_t = \sum_{i=1}^{D_t^*} h(U_{it} + M), where\ h(a) = \begin{cases} 1, a < 0 \\ 0, else \end{cases} \tag{6.9}$$

This chapter assumes that customers will return their product in the same period of getting fulfilled. In practice, customers may also probably keep and consume the products for several periods and then return them. In this case, such an amount of time can be absorbed into the reverse supply chain lead time L_r meaning that the reverse lead time essentially includes the time for reverse supply chain operations and the time for customers keeping it before return (see Turrisi et al., 2013).

After fulfilling demand, the retailer can update inventory level and work-in-process level in period t as I_t and WIP_t:

$$I_t = max(I_{t-1} + r_{t-L_r} + O_{t-L} - D_t, 0)$$ (6.10)

$$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-L} + r_{t-1} - r_{t-L_r}$$ (6.11)

where O_{t-1} is the order quantity placed in period $t - 1$, and r_{t-1} is the returned product in $t - 1$. Here the work-in-process comprises two types of products namely newly manufactured and returned products.

To make the replenishment decision, the company needs to forecast the future demand. The forecasting for replenishment is assumed as a simple exponential smoothing:

$$F_t = \theta * D_t + (1 - \theta) * F_{t-1}$$ (6.12)

with θ equal to 0.2 (Syntetos et al. 2011).

Finally, the company can make the replenishment decision by placing an order in period t. Consistent with Dominguez et al. (2019) and Tang and Naim (2004)'s type three model, O_t is formulated as:

$$O_t = max(0, (L + 1) * F_t - r_{t-L_r} - I_t - WIP_t)$$ (6.13)

The operations of the supply chain will generate different costs and revenue, and this chapter calculates the net profit to evaluate the closed-loop supply chain performance. Specifically, this chapter assumes the supply chain will generate a unit cost for producing a new product,

unit lost sales penalty cost for one unfulfilled order, unit holding cost in the forward supply chain, as well as unit cost occurring in the reverse supply chain. However, because there are different assumptions on reverse supply chain operations (see Govindan and Soleimani, 2017), the reverse supply chain costs can vary. As this model focuses on how online reviews influence the overall closed-loop supply chain performance, this chapter thus assumes a holistic unit cost for all types of reverse supply chain operations for a single return product, covering the activities spanning from collecting it back to the company, repackaging or refurbishing it if necessary, up to re-selling it to the customers. This chapter here terms this unit reverse supply chain cost for each returned product as ReC, abbreviating for 'unit Reverse supply chain Cost'. Therefore, the costs for the closed-loop supply chain include unit cost for producing a product, unit lost sales penalty cost, unit holding cost, and ReC.

Specifically, consistent with Chapters 4 and 5, this chapter assumes the product price is 1 as this price can lead to a positive sale but the product cannot cover the whole market. The cost structure for unit cost for producing a product, unit holding cost, and unit lost sales penalty in the forward supply chain is the same as those in Chapter 4. However, as reverse supply chain operations are taken into consideration, ReC can be the main influencer of the result. Therefore, extending the simulation experiments of Chapters 4 and 5, this chapter examines the different scenarios for ReC. Although some papers assume a relatively low ReC cost (Georgiadis et al., 2006), this study would argue that such cost can vary significantly depending on different products and industries. Therefore, ReC is changed from low to high to check if it can moderate the influence of online reviews on supply chain performance (see experiment design in Table 6.2). However, as the unit cost for producing a new product is assumed as 0.7 to be consistent with the previous Chapters, the highest ReC cost should not be close even exceed 0.7 otherwise the company will have little incentives to collect the return products instead of producing new ones. In addition, based on the practices, this chapter assumes a full refund policy so that the online retailer will refund the money equal to the sold price for returned products. This means the retailer cannot make profits from the customer return. The profit of the company thus can be derived as

$Total\ Profit = TotalRevenue - TotalHoldingcost - TotalLostSalesPeanlty - TotalReverseSCcost$ (6.14)

where $TotalRevenue$ is equal to the total money made by selling products (excluding the returned ones) minus the total cost for producing new products, and $TotalReverseSCcost$ is the total reverse supply chain cost, which is equal to the ReC cost multiplies the total volume of returned products.

6.4 Experimental design

Similar to Chapters 4 and 5, the simulation experiments start by considering the most important variables relevant to the closed-loop supply chain, and then the sensitivity analysis is conducted for other contextual parameters. There are three variables considered in the simulation, namely online review adoption, quality estimation, and ReC.

As this chapter aims to evaluate the influence of online review adoption on closed-loop supply chain performance, the main independent variable is still adopting/not adopting online reviews. Further, as argued in Chapters 4 and 5, customers can have a biased estimation on true mean product quality (i.e. q_u), the experiment design in this chapter still considers this variable as important and examines its impact in the simulation. However, different from Chapters 4 and 5, three rather than two scenarios namely underestimation, accurate estimation, and overestimation are included in the simulation experiment. The rationale is that, in the previous two chapters, it can be seen from Equation (4.3) that if customers accurately estimate the quality before purchase, there is no influence between adopting and not adopting online review as every customer has the same probability in posting a review, and thus the rating will converge to the true mean quality. However, in this chapter, the probability of posting reviews is different between customers when product return is considered (reflected in the empirical results in Sahoo et al., 2018), the rating shown in the system is not necessarily convergent to the true mean quality. Therefore, it is necessary to include an accurate estimation scenario to achieve an exhaustive experiment design. Consistent with previous chapters, it is assumed the q_u is equal to 0.5, while the under-estimated quality value is equal to 0.3 and the over-estimated value to 0.7. Finally, as the value of ReC cost is a variable to measure the expense generating in the reverse supply chain operations and directly influence the profit (Dutta et al., 2020; Zhou and Zhou, 2015; Dowlatshahi, 2010), it is considered as an important factor in this study as

well. Three scenarios of low, medium, and high ReC cost levels are examined in the simulation experiments as $\{0.01, 0.3, 0.6\}$.

In total, three variables are considered and thus there are $2 * 3 * 3 = 18$ scenarios. In addition, for each scenario, 5 replications are conducted, leading to the total experiments to 90. For each experiment, 20000 periods are simulated, with the first 3000 as the warm-up periods. The R codes are in Appendix A1, and the total running time for the simulation experiments is approximately 4 working weeks. ANOVA is applied to the results to check the main and interaction effect of different parameters on SC performance. The values of independent variables as well as parameters are all listed in Table 6.2.

Parameters	
True mean product quality (q_μ)	0.5
Product quality standard deviation (σ_μ)	0.2
Customer preference (x_{it})	$U \sim (0,1)$
Product price (p)	1
Customer return cost (M)	0.15
Probability of review posting for customers keeping product	74%
Forecasting smoothing parameters (α)	0.2
Lead time (L)	4
Unit cost for producing a product	0.7
Unit holding cost per product each period	0.0045
Unit lost sales penalty cost	0.35
Customers per period (N)	50
Probability of review posting for customers returning product	100%

Independent variables

Online review adoption {Adopt, Not Adopt}

Quality estimation (q_μ^e) {Under-estimation (0.3), Accurate (0.5), Over-estimation (0.7)}

Unit reverse supply chain cost (ReC) {Low (0.01), Medium (0.3), High (0.6)}

Performance measure

Total Profit

Table 6.2 Experiment parameters and variables for closed-loop supply chain

6.5 Model validation and verification

In this model, thorough validation and verification are conducted. Apart from adopting the validation and verification steps in Chapters 4 and 5, the simulation programs for the supply side model were also verified based on the values in Tang and Naim (2004), and it showed that the model in this chapter is of good accuracy.

6.6 Simulation results

The ANOVA results in Table 6.3 indicate all three factors and their interaction effects pose a significant influence on closed-loop supply chain performance in a 95% confidence interval level. Shapiro-Wilk test and Levene's test are used to check the assumptions of normality and homogeneity of variance and no violation of either assumption is detected.

	Df	Sum Sq	Mean Sq	F value	p value
OR	1	$2.24*10^9$	$2.24*10^9$	$7.78*10^4$	<0.001
QE	2	$8.23*10^9$	$4.12*10^9$	$1.43*10^5$	<0.001
ReC	2	$5.95*10^9$	$2.98*10^9$	$1.03*10^5$	<0.001
OR*QE	2	$8.17*10^9$	$4.09*10^9$	$1.42*10^5$	<0.001
OR*ReC	2	$4.58*10^8$	$2.29*10^8$	$7.96*10^3$	<0.001

QE*ReC	4	$2.25*10^9$	$5.62*10^8$	$1.95*10^4$	<0.001
OR*QE*ReC	4	$2.24*10^9$	$5.59*10^8$	$1.94*10^4$	<0.001
Residuals	72	$2.07*10^6$	$2.88*10^4$		

Remarks: OR stands for online review adoption; QE stands for quality estimation; ReC stands for ReC level.

Table 6.3 ANOVA results

As the focus of this chapter is online review adoption, only main and interaction effects related to online review adoption will be analysed. First, the main effect of online review adoption in closed-loop supply chain performance is depicted in Figure 6.3, indicating that on average, adopting online reviews will lead to slightly more profit. Specifically, the average profit for the closed-loop supply chain is 113543 when adopting online reviews while the profit is 103571 without online reviews.
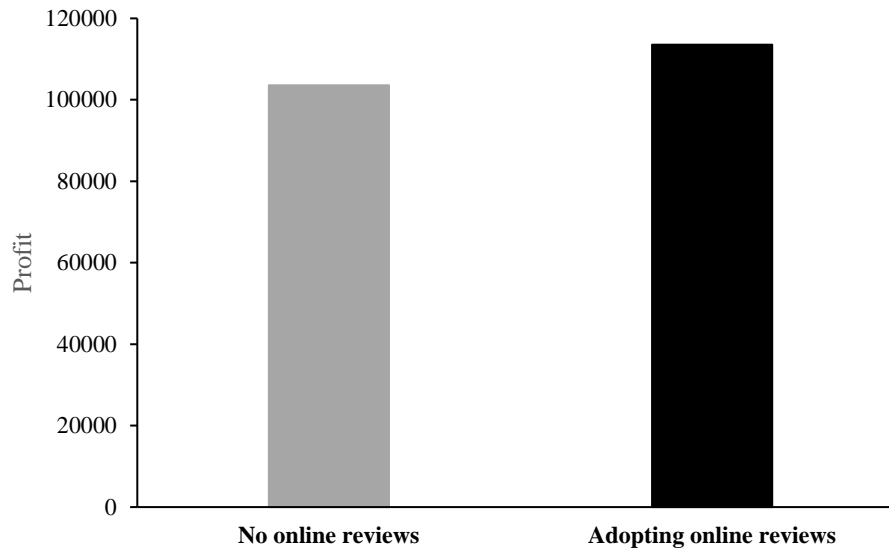
Figure 6.3 The main effect of online review adoption on supply chain profit

Second, the first order interaction between online review adoption and the other two variables in Figure 6.4 demonstrates that in different scenarios, the adoption decisions may vary. From ReC perspective, adopting online review is always superior, and a higher ReC level leads to a larger profit difference than the lower ReC (Figure 6.4 (a)). However, from the quality estimation perspective, the decision depends on customer estimation bias (Figure 6.4 (b)). Specifically, when customers can accurately estimate the quality, adopting online reviews is not an influential factor for profit. When customers under-estimate the product quality,

adopting online reviews can lead to more profit, while such a decision generates lower profit when customers over-estimate the quality. Such a result is probably consistent with intuition, and a potential explanation for it is that when customers under-estimate the quality, online reviews correct such bias and thus increase the total sales, leading to the profit increase. On the contrary, when customers over-estimate the quality, online reviews correct their estimation and decrease the total sales, resulting in profit loss. Such an explanation may suggest a quite straightforward way to adopt online review. To further check if this explanation is correct, it is worth further checking the second order interaction.

(a) Interaction between ReC and online review adoption

(b) Interaction between Quality estimation and online review adoption
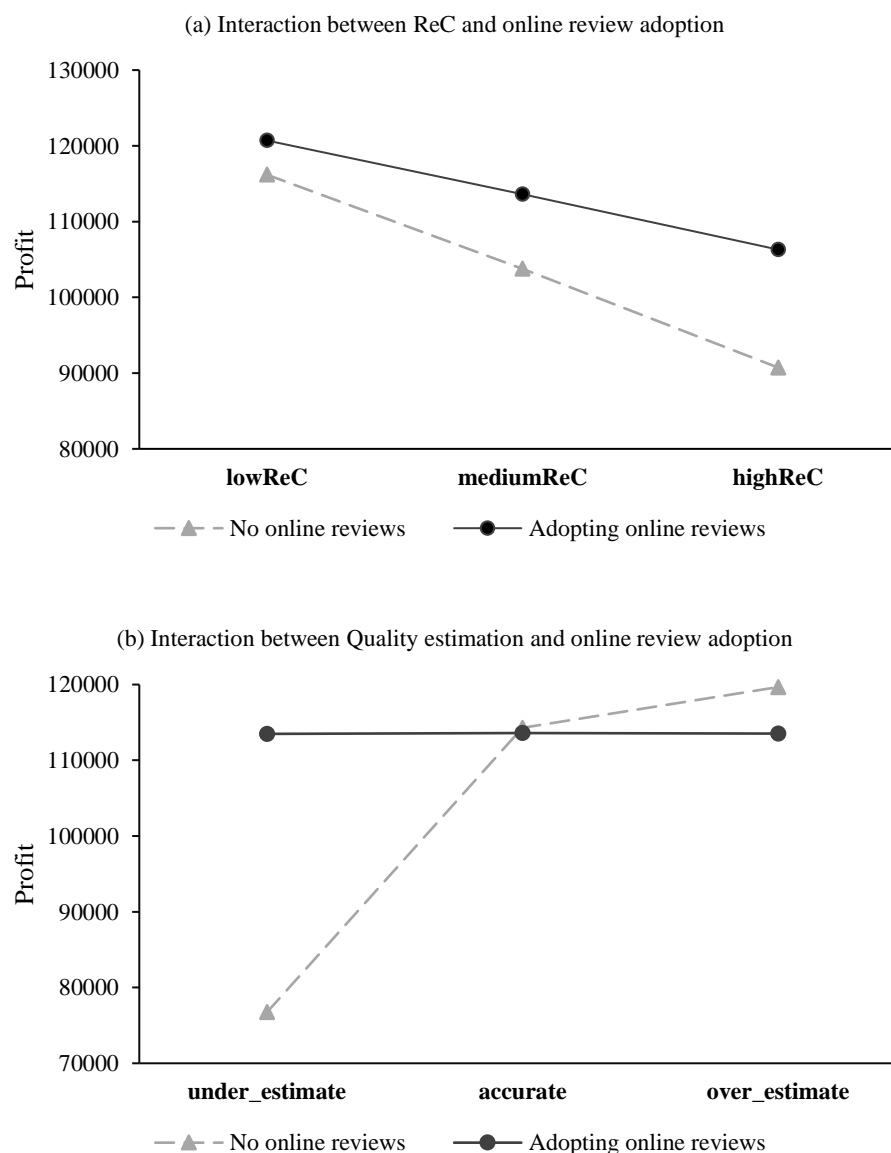
Figure 6.4 The first order interaction effects

Visualisation of the second order interaction effect is presented in Figure 6.5. Specifically, when customers accurately estimate the quality, adopting online review or not does not post significant influence on closed-loop supply chain profit, which is consistent with the above analysis. This means that although the rating probability differs between different types of customers, the influence of such difference can be negligible. When examining the under-estimation and over-estimation scenarios, more insights can be obtained. It can be observed graphically that for under-estimation, adopting online reviews is always superior, but it can bring higher profit difference when the ReC is lower. This result could also mean if customers under-estimate the quality, managers should always adopt online reviews no matter the reverse supply chain efficiency is high or low. More interestingly, for over-estimation, the results present distinct features for different ReC levels, and adopting online review brings profit down when ReC is in the low and medium level but can lead to higher profit when ReC is high. In addition, the second order interaction effect here shows that, compared with ReC, the profit seems to be more strongly influenced by quality estimation. To sum up, from Figure 6.5, the whole results look quite diverse, and thus to further investigate the causal relationship behind it, a revenue-cost analysis is conducted.
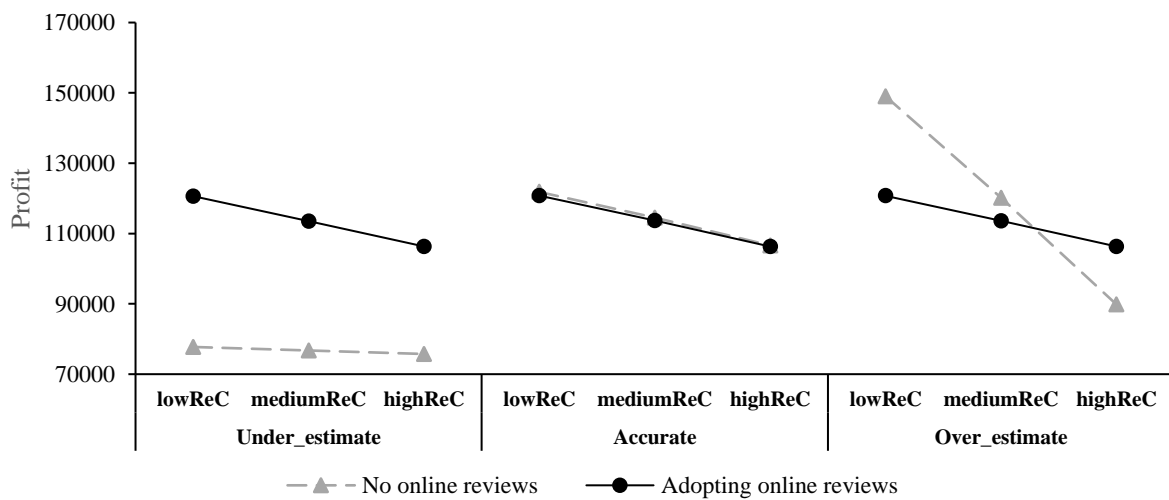
Figure 6.5 The second order interaction effect among online review adoption, ReC, and Quality estimation on closed-loop supply chain profit

In Figure 6.6, the differences in total revenue, costs, and profit between adopting and not adopting online reviews are presented in the waterfall graphs, and each column stands for the number equal to the corresponding value of adopting online reviews minus the value without

online reviews. In other words, if a column shows the number is positive (negative), it means such a value is higher (lower) when online reviews are adopted. The numerical relationship by equation (6.14) indicates that the value of total profit difference (which is 'Profit' in Figure 6.6) is equal to the value of total revenue difference ('Revenue' in Figure 6.6) minus the summation of total holding cost difference ('Holding cost' in Figure 6.6), total reverse supply chain cost difference ('ReverseSCCost' in Figure 6.6), and total lost sales penalty difference ('LostSales' in Figure 6.6) values in each scenario. The initial observation of Figure 6.6 indicates that the differences in total holding cost and total lost sale penalty between the two scenarios are nearly invisible, meaning that these two cost differences are not the influential factors for online review adoption decision. However, the other two, namely the total revenue difference and total reverse supply chain cost difference, are the important reasons for closed-loop supply chain profit difference, which explains the results in Figure 6.5.
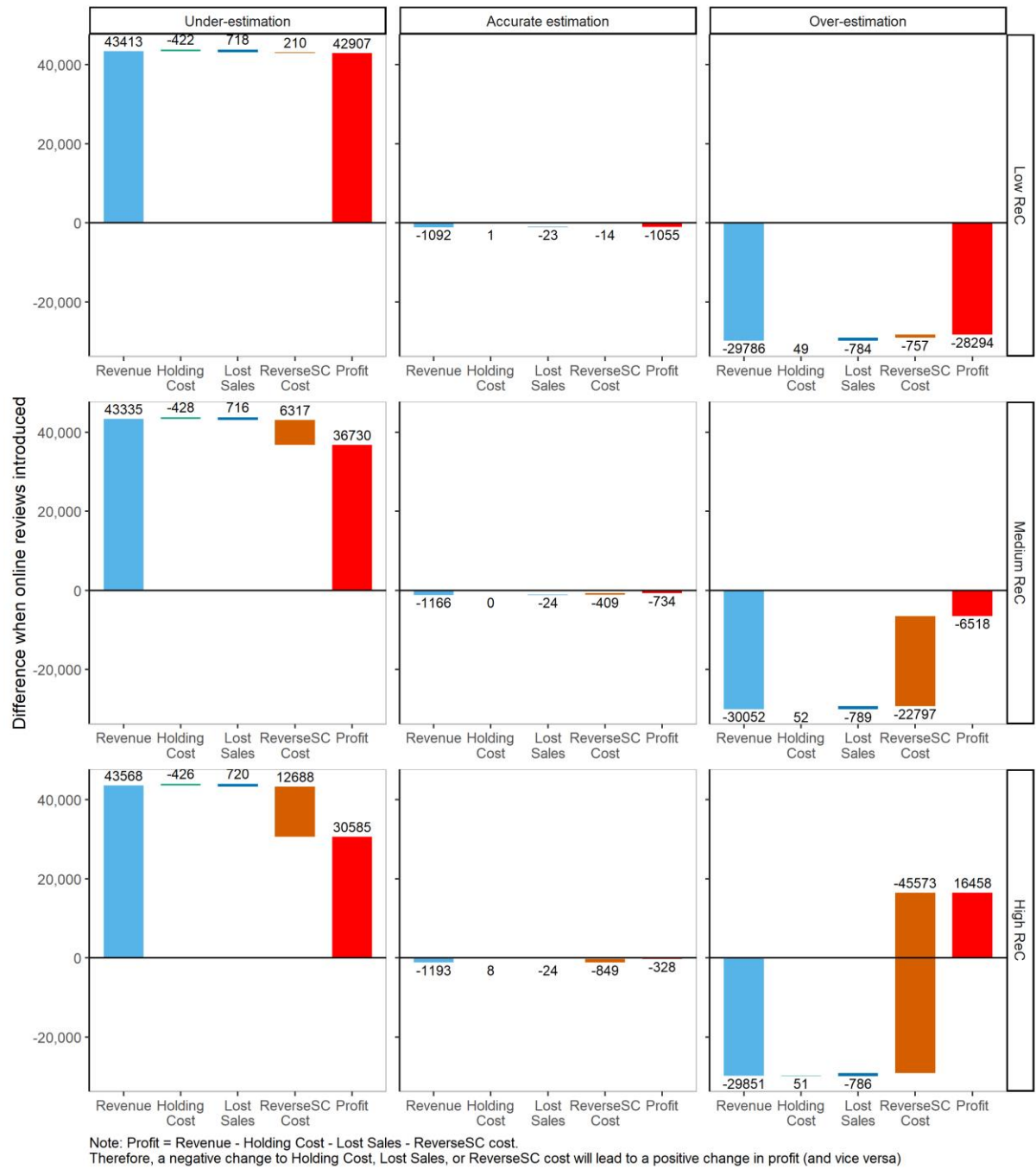
Figure 6.6 The difference between adopting and not adopting online reviews in total revenue, costs, and profit of the supply chain

Specifically, when customers accurately estimate the quality, both differences (total revenue difference and total reverse supply chain cost difference) are nearly zero, leading to a similar profit between adopting and without online reviews. When customers under-estimate the quality, it can be identified that the difference in total revenue is always higher than the difference in total reverse supply chain cost, meaning that online review should be always

adopted. Here, online review adoption influences the supply chain profit from two contradictory ways. On the one hand, the adoption increases the total revenue as it corrects under-estimation bias. On the other hand, it also increases the product return due to the increased sales, leading to higher total reverse supply chain cost. When ReC level is low, the influence on revenue increase is significant but total reverse supply chain cost increase is negligible. With the increase of ReC level, the magnitude of total revenue increase keeps the same, but the increase in the total reverse supply chain cost gets more significant. However, the results in Figure 6.6 show that for under-estimation even in the high ReC level, the total revenue increase is still more significant than the increase in the total reverse supply chain cost, leading online review adoption always to a superior decision for the under-estimation scenario.

On the other hand, when quality is over-estimated, the adoption of online reviews influences the profit difference in an opposite direction compared with the under-estimation scenario. Specifically, adopting online reviews in the over-estimation scenario brings lower product sales as well as less product return compared with not adopting online reviews. When ReC level is low, online review adoption mainly brings down the total revenue but works little on reverse supply chain cost reduction, leading adopting online reviews to an inferior decision in terms of increasing supply chain profit. However, with the increase on ReC level, the total reverse supply chain cost starts playing an important role and the influence of online review adoption on decreasing total reverse supply chain cost becomes more significant. At the high ReC level, it can be found that the reverse supply chain cost saving induced by online review adoption eventually leads to higher profit for the supply chain compared with not adopting online reviews, making online review adoption a superior decision.

6.7 Sensitivity analysis

In this section, sensitivity analysis is conducted to examine the influence of different values of four parameters, namely customer return cost M, probability of review posting for customers keeping the products, unit holding cost, and unit lost sales penalty. The values of the four parameters are changed to examine how the different values of these parameters can bring impacts on the simulation findings. Conducting sensitivity analysis for unit holding cost and

unit lost sales penalty is consistent with Chapters 4 and 5, while sensitivity analysis for M and probability of review posting for customers keeping product is based on the following reasons.

For M, it is because in practice, the customer return cost can vary depending on different return policies and return operations, and customers can spend different time and expense for returning products to different retailers. However, it is arguable that in E-commerce, the product return policy and customer return cost are not determined solely by retailers, but also by the platforms. For example, most products sold in Amazon follow the return policy made by the platform rather than the individual retailer (this can be found in the Returns and Refunds service information in Amazon.co.uk). When customers need to return products, they also have to contact the platform first. In other words, the customer return cost may not be fully controllable by retailers themselves, which is the reason that M is not considered in the simulation experiments but examined in the sensitivity analysis.

The reason for conducting sensitivity analysis on the probability of review posting for customers keeping product is because the empirical data of it is quite rare. To the best of the author's knowledge, the only study which records the probability difference for review posting between customers returning and keeping products is Sahoo et al. (2018). However, as they just empirically examined three brands of a specialty retailer, it is possible in practice that such kind of probability difference can vary in other product categories. Therefore, it is necessary to check if the findings are sensitive to changes in the probability difference.

6.7.1 Sensitivity analysis for customer return cost (M)

In this subsection, the different scenarios of customer's return cost M are considered. M is assumed as 0.15 in the simulation experiments, and here different values including $M = 0.01$ and $M = 0.3$ are examined in the sensitivity analysis. Table 6.4 depicts the SC profit under different values of M. Consistent with Chapters 4 and 5, 'Indifference' means the profit difference between adopting and not adopting online reviews is within $\pm2.5\%$, while 'Adopt' means the profit difference is higher than 2.5% while 'No' means the difference lower than -2.5%. Overall, the sensitivity analysis indicates the simulation results are sensitive to the change of M in some scenarios which are highlighted in **bold** in Table 6.4.

ReC	Quality Estimation	M	Profit of adopting online reviews	Profit of no online reviews	Adoption decisions?
Low	Under-estimation	0.15	120631	77724	Adopt
		0.01	117530	97165	Adopt
		0.3	124559	75343	Adopt
	Accurate	0.15	120754	121809	Indifference
		0.01	117437	118380	Indifference
		0.3	124693	125049	Indifference
	Over-estimation	0.15	120723	149017	No
		0.01	117467	123103	No
		0.3	124697	166204	No
Medium	Under-estimation	0.15	113506	76776	Adopt
		0.01	**80515**	**85040**	**No**
		0.3	123148	75184	Adopt
	Accurate	0.15	113741	114475	Indifference
		0.01	**80618**	**78762**	**Adopt**
		0.3	123254	123686	Indifference
	Over-estimation	0.15	113606	120124	No
		0.01	**80619**	**40843**	**Adopt**
		0.3	123041	155954	No
High	Under-estimation	0.15	106329	75744	Adopt
		0.01	**42416**	**72648**	**No**
		0.3	121540	75157	Adopt
	Accurate	0.15	106289	106616	Indifference
		0.01	**42694**	**38080**	**Adopt**
		0.3	121445	121918	Indifference
	Over-estimation	0.15	106308	89850	Adopt
		0.01	42673	-44203	Adopt
		0.3	**121607**	**145491**	**No**

Table 6.4 Sensitivity analysis to M

In total, as three different levels of M are selected, this sensitivity analysis contains 27 comparisons between adopting and not adopting online reviews. The table reflects: (1) when ReC is low, the online review adoption decisions revealed from simulation results are insensitive to the change of M; (2) when ReC is medium, the decisions revealed from

simulation results are insensitive only when M is medium (0.15) and high (0.3); (3) when ReC is high, the simulation results are more sensitive to the change of M compared with medium or low ReC. Overall, the sensitivity analysis presents some complicated and nonlinear properties of the influence from M on the online review adoption decisions.

To interpret the causal relationship between M and online review adoption decisions, the product fulfilled demand, product return, and sales under each scenario are listed in Table 6.5. The fulfilled demand means the fulfilled customer orders, while the sales are the fulfilled orders minus the product return. In other words, the revenue is based on sales instead of the fulfilled product demand. Here, other terms including lost sales and inventory volumes are not listed and analysed, as the simulation results in Section 6.6 (Figure 6.6) indicate they are not the influencers of the profit difference between adopting and not adopting online reviews.

	Fulfilled Demand			Return			Sales (Fulfilled Demand minus return)		
	Not Adopt	Adopt	Difference (Adopt minus Not adopt)	Not Adopt	Adopt	Difference (Adopt minus Not adopt)	Not Adopt	Adopt	Difference (Adopt minus Not adopt)
Low ReC									
under-estimate									
M=0.01	373149	531078	157930	41684	127096	85411	331464	403982	72518
M=0.15	268288	434008	165720	3390	24425	21035	264898	409583	144686
M=0.3	257310	427126	169815	370	5189	4819	256941	421937	164996
accurate									
M=0.01	543446	530747	-12699	136131	127065	-9066	407316	403682	-3634
M=0.15	439499	434428	-5071	25824	24403	-1421	413674	410025	-3650
M=0.3	428860	427579	-1280	5257	5174	-82	423603	422405	-1198
over-estimate									
M=0.01	713499	530984	-182515	283000	127205	-155795	430499	403779	-26720
M=0.15	609459	434460	-174999	100233	24531	-75702	509226	409929	-99297
M=0.3	599116	427552	-171563	34957	5142	-29815	564159	422410	-141748
Medium ReC									
under-estimate									
M=0.01	372748	530979	158231	41566	127300	85733	331182	403679	72497
M=0.15	268287	433803	165517	3325	24382	21057	264962	409422	144460
M=0.3	257148	427220	170072	365	5081	4716	256783	422140	165356
accurate									
M=0.01	543279	530900	-12380	136277	127095	-9183	407002	403805	-3197
M=0.15	439911	434667	-5244	25784	24422	-1362	414127	410245	-3882
M=0.3	429374	427753	-1621	5242	5170	-72	424133	422584	-1549
over-estimate									

M=0.01	713588	531251	-182337	283372	127251	-156120	430216	403999	-26217
M=0.15	610168	434000	-176167	100296	24306	-75990	509872	409694	-100178
M=0.3	598793	426869	-171924	34982	5088	-29894	563812	421782	-142030
High ReC									
under-estimate									
M=0.01	373100	531112	158011	41588	127238	85649	331512	403874	72362
M=0.15	268155	434534	166379	3328	24475	21147	264827	410059	145231
M=0.3	257387	427038	169651	374	5105	4731	257013	421933	164920
accurate									
M=0.01	543304	530838	-12466	136067	126842	-9226	407237	403997	-3240
M=0.15	439751	434361	-5391	25871	24455	-1415	413881	409905	-3975
M=0.3	428653	426905	-1748	5226	5159	-67	423427	421746	-1682
over-estimate									
M=0.01	713537	530904	-182634	283402	126893	-156510	430135	404011	-26124
M=0.15	609651	434178	-175473	100337	24382	-75956	509314	409796	-99518
M=0.3	598971	427328	-171643	35005	5129	-29877	563966	422199	-141766

Table 6.5 Demand, return, and sales in each scenario

Online review adoption decision is determined by whether the profit difference between adopting and not adopting online review is positive. The profit difference, based on analysis in Section 6.6, is mainly determined by total revenue difference and total reverse supply chain cost difference. Therefore, as the sales volume is directly linked to revenue while return volume to reverse supply chain cost, to interpret the sensitivity analysis, it is necessary to focus on how M influences the sales difference and return volume difference between adopting and not adopting online reviews.

In Table 6.5, three numerical observations of M can be generated to link each type of difference, which aids sensitivity analysis interpretation. First, although M influences fulfilled demand as well as sales, its influence on the *fulfilled demand difference* looks weak as the different levels of M bring similar fulfilled demand differences in the same ReC and customer estimation. Second, different levels of M can influence the return difference, and the lower the M is, the higher the *absolute* difference is. Third, although M can influence the sales difference, it can be found the sales difference always has the same sign of the fulfilled demand difference. The third observation, in other words, means that the major influence on the sales difference comes from the quality estimation bias, and such influence is stronger than what different levels of M post.

Based on the above three observations, the results of sensitivity analysis can be explained. As different levels of M mainly influence return difference, when ReC is low, no matter how high or low the return difference is, it posts little impact on profit difference. Therefore, when ReC is low, the simulation results are insensitive to M. When ReC is medium or high, the returned product volume generates higher total reverse supply chain cost thus makes simulation results sensitive to the change of M. Specifically, when ReC is medium and M is medium (0.15) and high (0.3), the return volume difference is small (compared with when M is low (0.01)). Therefore, the online review adoption decisions are determined mainly by quality estimation, making the simulation results to be insensitive. When ReC is medium but M is low (0.01), the profit difference is determined by return difference (proportional to the total reverse supply chain cost difference) and sales difference (proportional to the total revenue difference) together. As Table 6.5 shows, when ReC is medium, the absolute value of return difference under $M = 0.01$ is very high, making the simulation results do not hold. When ReC is high, similar reasoning can be applied to return difference and sales difference to explain why the simulation results are sensitive to some scenarios.

Apart from the explanation of the results of sensitivity analysis, it is worth noting that when ReC is medium or high and when customers *accurately* estimate the product quality, the adoption decision is 'Adopt' when M is low (0.01). This means even customers accurately estimate the quality, online reviews should be adopted. This is a different finding inconsistent with the previous results in Chapters 4 and 5 in which the adoption decision is always indifferent when quality is accurately estimated. This is because, in this chapter, the quality reflected in the online reviews is essentially not equal to the true quality but slightly lower, as customers who are not satisfied and return the product have a higher probability of posting. Therefore, when customers accurately estimate the product quality, compared with not adopting online reviews, adopting online reviews essentially *decreases* customers' estimation on quality before purchase and thus reduces the number of unsatisfactory customers as well as product return. As such influence is small, it is not visible when ReC is low. However, when ReC is higher, the return reduction saves the total cost for the reverse supply chain and thus increases the profit, which leads the online review adoption to a superior choice.

The inconsistency in the adoption decisions for accurate estimation between this chapter and previous chapters probably indicates the need to modify the definitions of under-estimation and over-estimation. Up to this section, the under-estimation is defined as the customer quality estimation without online reviews is lower than the true mean quality while the over-estimation is defined as the opposite. However, even though online reviews are adopted, what customers can see before purchase is never the true mean quality but the quality reflected in the online reviews. Therefore, a more inclusive definition is to re-define under-estimation as 'the quality estimated by customers without online reviews is lower than the quality reflected in online reviews in system steady state' while the over-estimation is defined as the opposite. Through this modified definition, the results of sensitivity analysis in this chapter are more interpretable. What should be noted is that this definition modification does not post any difference on the definition of under-estimation and over-estimation used in Chapters 4 and 5, as in those two chapters the rating will converge to the true mean quality after transient periods so the previous definition and modified definition are the same under the assumption of Chapters 4 and 5. The following sensitivity analysis will further discuss this modified definition of under-estimation and over-estimation.

6.7.2 Sensitivity analysis for probability of posting when customers keep products

To perform the sensitivity analysis, the probability of review posting for customers keeping product is varied from 0.74 to 1 and to 0.48, respectively. The rationale to adopting these two values is as follows. As the highest value of the probability is 1 (i.e. every customer keeping the product will post a review), it is used as an upper bound to test the result robustness. Symmetrically, the lower bound is calculated. In other words, the difference between 0.74 and 1 (i.e. 0.26) is equal to that between 0.48 and 0.74 (i.e. 0.26). It should be noted that this is essentially a very wide range comparing with the empirical data in Sahoo et al. (2018).

Table 6.6 indicates that the majority of the results is insensitive to the probability of posting for customers keeping products, except for one inconsistent result when ReC is low and when customers accurately estimate the product quality (highlighted in **bold** in Table 6.6). Based on the above discussion, it is easy to explain the reason. When the probability of posting for customers keeping the products is very low, the reviews posted by customers who are unsatisfied and return the products take increasing proportion, leading the quality reflected in

online reviews lower than the true mean quality. In other words, although customers accurately estimate the true quality without online reviews, they essentially *over-estimate* the quality reflected by online reviews. Following the modified definition, this is essentially the modified over-estimation scenario. The consequence is that, compared with no online reviews, adopting online reviews makes customers decrease their estimation on product quality and thus decrease the product sales as well as return. However, as ReC is low, the return decrease does not lead to dramatic reduction to the total reverse supply chain cost to mitigate the sales loss. Therefore, adopting online reviews lead to profit decrease under such a scenario.

ReC	Quality Estimation	Prob	Adopting online reviews	No online reviews	Adoption decisions?
Low	Under-estimation	0.74	120631	77724	Adopt
		0.48	118302	77724	Adopt
		1	121863	77724	Adopt
	Accurate	0.74	120754	121809	Indifference
		0.48	**118353**	**121809**	**No**
		1	121847	121809	Indifference
	Over-estimation	0.74	120723	149017	No
		0.48	118432	149017	No
		1	121838	149017	No
Medium	Under-estimation	0.74	113506	76776	Adopt
		0.48	111975	76776	Adopt
		1	114315	76776	Adopt
	Accurate	0.74	113741	114475	Indifference
		0.48	111824	114475	Indifference
		1	114351	114475	Indifference
	Over-estimation	0.74	113606	120124	No
		0.48	111920	120124	No
		1	114584	120124	No
High	Under-estimation	0.74	106329	75744	Adopt
		0.48	105384	75744	Adopt
		1	106785	75744	Adopt
	Accurate	0.74	106289	106616	Indifference
		0.48	105445	106616	Indifference
		1	106688	106616	Indifference
	Over-estimation	0.74	106308	89850	Adopt

0.48	105168	89850	Adopt
1	106678	89850	Adopt

Table 6.6 Sensitivity analysis on the probability of posting for customers keeping the products

It can be observed that using the modified definition for under-estimation and over-estimation can better explain the online review adoption decisions for the closed-loop supply chain. As the modified definition is the same as the previous definition under the Chapter 4 and 5 assumptions, the following texts will adopt the modified definition of under-estimation and over-estimation. Accordingly, the accurate estimation will also be defined as the quality reflected in online reviews in steady state is the same as customer quality estimation without online reviews. Under such a case, adopting or not adopting online reviews will be indifferent. In Section 6.8, the modified definition will be adopted to explain the overall influence of online reviews on closed-loop supply chain profitability.

6.7.3 Sensitivity analysis for unit holding cost and unit lost sales penalty

Consistent with Chapters 4 and 5, unit holding cost changes to 0.009 and to 0 to perform the sensitivity analysis while unit lost sales penalty to 0.7 and to 0. The sensitivity analysis for unit holding cost and unit lost sales penalty indicates that the results are insensitive to the change of both. As the sensitivity analysis table is long and all the results are insensitive, the table is thus omitted.

6.8 Discussion

In this section, the simulation results are discussed to partly form the answer to **RQ3**. Meanwhile, the simulation model in this chapter is discussed to extend the modelling framework proposed in Chapters 4 and 5 to closed-loop supply chain configurations and contributes to the development of the answer to **RQ2**.

6.8.1 Discussion on simulation results

Based on the simulation results in Section 6.6 as well as the sensitivity analysis in Section 6.7, this section discusses how online review adoption can influence supply chain profitability. Although the influence of online reviews in closed-loop supply chain performance is still a realisation of the connecting-tool mechanism, the way online reviews influence the performance in this chapter is much different from that in Chapters 4 and 5. Figure 6.7 presents the causal relationship between online review adoption and closed-loop supply chain profit. According to the discussion in sensitivity analysis, the under-estimation is now defined as customer estimation on quality without online reviews is lower than the quality reflected in online reviews in steady state, while the over-estimation is defined as the opposite. Therefore, the under-estimation or over-estimation is not only determined by the customer estimation on true mean quality but also by the probability of review posting for different types of customers.
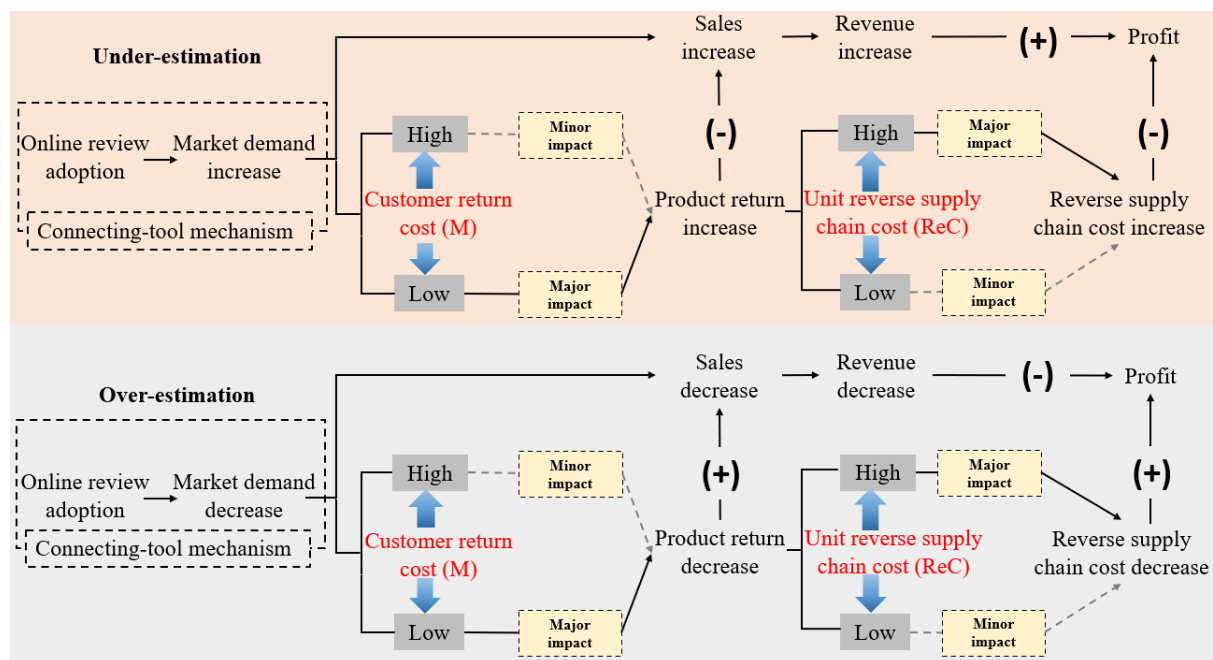
Figure 6.7 Influence of online reviews on closed-loop supply chain profit

Figure 6.7 demonstrates that, when an under-estimation scenario occurs, adopting online reviews can increase the market demand. The increased demand will bring higher sales as well as more customer returns. When the customer return cost *M* is high, fewer customers will return the products, which leads to a small magnitude of product return increase. On the contrary, when *M* is low, more customers will return, and a larger return increase is expected.

Subsequently, the increased returned products simultaneously lead to a decrease in sales increase (and thus decrease in revenue increase) and the increase in the total reverse supply chain cost. Especially when the unit reverse supply chain cost ReC is high, the total reverse supply chain cost will be increased dramatically. Finally, the profit of the supply chain is determined by the relative increase in total reverse supply chain cost and total revenue. When the increase in total revenue is higher than the increase in total reverse supply chain cost, adopting online reviews is a superior decision, otherwise not adopting them is better. When an over-estimation scenario occurs, the causal relationship works as the opposite, and the online review adoption decision is determined by the relative decrease in revenue and total reverse supply chain cost. To sum up:

> *In a closed-loop supply chain, online review adoption significantly influences supply chain profitability by changing total supply chain revenue and total reverse supply chain cost, and such influence is moderated by quality estimation, unit reverse supply chain cost, and customer return cost.*

Based on the results presented, this chapter can have several implications for managers to make better online review adoption decisions under different scenarios and improve closed-loop supply chain management practices. First, this chapter indicates that the decision on online review adoption is complicated and influenced by many factors rather than governed by intuition. In other words, an intuitive decision can work as adopting online reviews when customer expectation on quality is lower than the true product quality but not adopting reviews when customers have higher expectation of the true quality. Such 'naïve' thought can only be true when closed-loop supply chain operations and the relevant cost are not considered in the system, otherwise managers should make adoption decisions based on the relationship in Figure 6.7. Therefore, this chapter thus raises awareness of the impact of online reviews from a supply chain system perspective to alert managers considering all relevant costs before deciding to adopt online reviews.

Second, this chapter suggests the importance of decreasing the ReC, and this is especially true in the under-estimation scenario. When customers have an under-estimation bias on quality, companies need a tool to quickly correct such bias, and online reviews are one of the best choices. Therefore, to guarantee the effectiveness of online review adoption, managers need to

decrease the ReC level so that the profit will not be diminished by the significant increase in total reverse supply chain cost. Specifically, as ReC reflects the efficiency of the operations in the reverse supply chain, managers can design efficient reverse supply chain operations processes to reduce ReC, such as cooperating with reverse logistics companies and upgrading reverse SC information technology (Agrawal et al., 2015; Huang et al., 2013).

Finally, this chapter reveals that it is not always a good strategy to reduce the customer return cost M. M directly reflects the degree of customer return convenience, and E-commerce companies or platforms may pursue an easy product return strategy (low M) to attract prospective customers. However, the results drawn from this chapter suggest that, to make more profit/less loss, making customers easier to return products are not always optimal (Table 6.5 offers the evidence). Instead, under some situations, if companies or platform can choose their M levels, they need to simultaneously consider other factors including online review adoption decisions or reverse supply chain efficiency. This finding suggests companies or platforms may not always necessarily invest much in customer return service to make customer return process convenient, which directs a redesign of the management of the customer product return process.

6.8.2 Discussion on model building

In this chapter, the model extends Chapter 4 and includes the product return on the supply side. Figure 6.8 updates the OR-SCM framework in Chapter 4 to the closed-loop supply chain configuration.

Before purchase	
Estimated utility generation	1. Attributes based generation
	2. Distribution based generation
Review information interpretation and estimated utility update	1. Naïve interpretation (utility reflected in online reviews directly replaces estimated utility
	2. Weighted average interpretation
	3. Bayeisan update
Purchase decision	1. Updated estimated utility is greater than 0
	2. Updated estimated utility is greater than a threshold
Ordering behaviour	1. Order and wait to fulfill
	2. Order but leave if stock-out occurs

After purchase	
Real utility generation	1. Distribution based generation
	2. Attributes based generation
Behaviour of rating	1. All customers rate
	2. Probabilistic rating decision
	3. Rating-utility based rating decision
Value of rating	1. Naïve rating (rating is equal to realised quality)
	2. Utility based rating
	3. Distribution based rating
Product return	1. Utility based return
	2. Probabilistic return
	3. No return

Online review system	
Format of rating	1. Real number (which can even be negative)
	2. Real number with only limited decimal points (1- or 2-digits) retained
Update procedures of rating	1. Calculating average value for all previously posted ratings
	2. Calulating average value for posted ratings in a specific time window
Quality of rating	1. All ratings are real
	2. Rating with real and fake (promotional) rating

Retailer	
Inventory control	1. No inventory control
	2. Inventory control (e.g. order-up-to policy)
	3. Inventory control with reverse logistics
Competition	1. No competition
	2. Two or more retailers competing
	3. Competiting itself(multi-channel)
Pricing	1. Price taker
	2. Optimal pricing

Supplier	
Capacity of production	1. Unlimited
	2. Capacitated
Deficits of items	1. Equal quality for every item
	2. Occasional defective items
Sourcing	1. Single sourcing
	2. Daul sourcing
Pricing	1. Price taker
	2. Optimal pricing

Customers

Figure 6.8 OR-SCM framework for integrating online reviews in closed-loop supply chain

First, for the customer perspective, the modelling of *Before-purchase behaviours* changes in the customer purchase decisions where the decision criterion is not triggered by non-negative expected utility but the utility higher than a threshold influenced by the customer return cost (i.e. *M*). Compared with the models in Chapters 4 and 5, the customers are assumed as forward-looking customers (Anderson et al., 2009) who know the *M* and will take it into purchase decision making. It can be observed from the model formulation that the simulation process is more complicated than the previous two chapters, with more features of customers captured.

Second, a new variation of modelling *After-purchase behaviours* is added (i.e. product return). In this thesis, the way to model the product return decision is a 'utility-based return', consistent with previous literature (e.g. Sahoo et al., 2018; Anderson et al., 2009). However, it is also possible to simply model the return as a proportion of sales, which is a modelling approach frequently adopted in supply chain literature (e.g. Zhou and Disney, 2006; Tang and Naim,

2004; Hosoda et al., 2015). As the utility-based approach enables the deeper investigation on the relationship between customer return cost and online review information, it is chosen in this chapter. In addition to the customer product return, the rating process is changed as well. In Chapters 4 and 5, the customers, after receiving the products, have an equal probability of rating the product. However, based on Sahoo et al.'s (2018) empirical results where customers returning the product have a higher probability to post a review, the model in this chapter enables customers to have unequal rating probability.

Apart from the customer side, the modelling of *Online review system* remains unchanged, and the average value of all previously posted ratings is presented in the system. However, the *supply side* experiences a significant change because the returned product is considered. Compared with Chapters 4 and 5, the supply chain now becomes a closed-loop supply chain where both forward product flow and reverse flow need to be considered. The returned products now become a part of the system, and this leads to the change of the ordering rule where the reverse product flow needs to be considered in the replenishment processes (Turrisi et al., 2013; Tang and Naim, 2004).

6.9 Chapter summary

In this chapter, the influence of online review adoption on closed-loop supply chain performance is explored. Using closed-loop supply chain profit as the performance measure, this paper modelled and investigated the relationship between closed-loop supply chain profit and online review adoption decisions by simulation. On average, adopting online reviews can bring slightly higher closed-loop supply chain profit, but the different levels of customer quality estimation and the unit reverse supply chain cost ReC are also found to have significant moderation effects on such relationship. The simulation results are sensitive to customer return cost M but insensitive to customer rating probability difference. To sum up, the influence of online reviews on closed-loop supply chain performance is founded complicated but mainly impacts on changing total revenue and total reverse supply chain cost. The different dominance of revenue change and reverse supply chain cost change determines whether adoption online reviews can lead to higher profit. The findings of Chapter 6 form part of the answers to **RQ3**.

Meanwhile, the mathematical models in this chapter capture more elements compared with Chapters 4 and 5, enriching the modelling framework and form the answers to **RQ2**.

CHAPTER 7

CONCLUSION

7.1 Chapter summary

This chapter summarises the content of the whole thesis and provides the answers to research questions. In brief, this thesis aims to study the influence of adopting online reviews on supply chain performance. To meet this aim, the thesis has systematically reviewed literature related to online reviews in supply chain management, before combining supply chain modelling and online review modelling to conduct a hybrid simulation. The mathematical models are applied to evaluate the supply chain performance (i.e. profitability). These models are developed in R and increased in complexity by considering capacity constraints and product returns.

In this chapter, the research findings of previous chapters are reported briefly. After that, the contributions of this thesis are discussed, together with the academic and managerial implications. Finally, the limitations of this thesis are discussed and future directions are suggested.

7.2 Answers to the research questions

To fulfil the research aims, this thesis studied the following three research questions: (1) **What are the mechanisms by which online reviews influence supply chain performance?** (2) **How can online reviews be integrated into supply chain modelling?** (3) **How does the influence of adopting online reviews differ between supply chain configurations?** To answer them, different activities are conducted in each chapter. Specifically, Chapter 2 answers **RQ1**, and Chapters 4 to 6 address **RQ3**, with each chapter examining a different supply chain configuration. Also, the answer to **RQ2** is based on Chapters 3 to 6, where Chapter 3 developed a macro-level modelling framework while Chapters 4 to 6 enrich the framework with details. Before presenting the answer to each research question, to better explain how research aims

are satisfied, the research activities undertaken in each chapter and their connections with different **RQ**s are summarised in Table 7.1.

Chapters	Activities undertaken	Connections with RQs
Chapter 2	1. summarised current topics in online review research on supply chain management 2. proposed the mechanisms about how online reviews can influence supply chain performance 3. summarised current research method used in online review research on supply chain management 4. focus on mathematical modelling and summarised model structure and analytical techniques	**RQ1**
Chapter 3	1. discussed why the hybrid simulation by system dynamics and agent-based modelling suits online review research in supply chain management 2. developed a macro-level modelling framework to integrate online reviews to supply chain modelling.	**RQ2**
Chapter 4	1. found how online review adoption can influence the profitability of a supply chain and how such influence can be moderated by lead time and quality estimation. 2. based on the macro-level framework in Chapter 3, built a modelling framework for uncapacitated forward supply chain with online reviews	**RQ2, RQ3**
Chapter 5	1. found how online review adoption can influence the profitability of a capacitated supply chain and how such influence can be moderated by capacity constraint, lost sale penalty level and quality estimation. 2. built extended modelling framework for capacitated forward supply chain with online reviews	**RQ2**, **RQ3**
Chapter 6	1. found how online review adoption can influence the profitability of a closed-loop supply chain and how such	**RQ2**, **RQ3**

influence can be moderated by quality estimation and
unit reverse supply chain cost.

2. built an extended modelling framework for closed-
loop supply chain with online reviews

Table 7.1 Summary of chapter findings and connections to the research questions

In the following texts, the answers to each question are presented:

RQ1. What are the mechanisms by which online reviews influence supply chain performance?

Answer: Through a rigorous systematic literature review, three different functions of online reviews, namely customer-customer information sharing function, company-customer information sharing function, and company-company information sharing function, as well as their influence on different supply chain activities are found. Although the functions and supply chain activities influenced vary significantly in different studies, two generic mechanisms, called data-source mechanism and connecting-tool mechanism, have a good explanatory power to address how online reviews can influence the performance of the overall supply chain system.

Specifically, data-source mechanism explains that the influence of online reviews is generated from the review content posted by customers, and the content can be analysed by companies to enhance their sensing capability to improve supply chain performance. However, to leverage the online review functions and let them positively contribute to the sensing capability, companies need to equip themselves with high supply chain online review analytic capability. The sampled papers show that the influence of online reviews on supply chains reported in most of the empirical studies on online review mining can be explained by this mechanism, but none of modelling papers are found related to it. The discovery of the data-source mechanism is believed to be able to help managers make better decisions in utilising business data analysis (especially big data analysis in current days) for online reviews to enhance supply chain performance, such as informing their decisions on training data analyst, building infrastructures, developing new analytic techniques, etc. Also, this mechanism also raises awareness of the managers that the rich information from online reviews is not also beneficial, and only the content which can be correctly interpreted and utilised can lead to positive impact on the supply chain.

Connecting-tool mechanism, on the other hand, explains that the influential power of online reviews comes from forming richer communications and connections between different players in the supply chain (i.e. customer, retailer, supplier, etc.). The adoption of online reviews reduces the barrier of supply chain information sharing and leads to more effective and efficient communication, which then influences the supply chain performance. In certain situations, better communication can lead to significant improvement in supply chain performance. However, revealed from this mechanism, the online review influence on the supply chain will not always be positive. For example, richer information can probably correct the over-estimation bias of customers and result in the loss of supply chain profit. The connecting-tool mechanism can explain the influence of online reviews reported in some of the empirical studies and all mathematical modelling studies. Interestingly, most of the modelling papers found the 'double-edge sword' influence of online reviews where both positive and negative impacts can be posed to supply chain performance because of online review adoption. The models in Chapters 4 to 6 are also the realisation of this mechanism and both positive and negative influences of online reviews are discovered.

It should be noted that the simulation studies in this thesis only focuses on connecting-tool mechanism (to be discussed in the answer to **RQ3**) without considering the data-source mechanism to follow the current stream of existing modelling literature in this field. However, it is also very promising to study data-source mechanism through a mathematical modelling lens in the future, such as examining the optimal investment in capabilities of analysing online reviews.

RQ2. How can online reviews be integrated into supply chain modelling?

Answer: To answer **RQ2**, a generic framework called OR-SCM is established to integrate online reviews in supply chain modelling based on the work from Chapters 3 to 6. Specifically, the OR-SCM framework is built by combining the APIOBPCS and online review modelling where the supply side is modelled as a periodic review system while the demand side is derived from customer utility under the influence of online reviews. However, to better present the details of OR-SCM, it is worth having a general picture of the simulation models first and demonstrate why the models built in this thesis can contribute to existing literature.

In Figure 7.1, the models developed in this thesis are visualised in a swimlane graph. From the figure, five components can be identified: customer before-purchase behaviour, and customer after-purchase behaviour, online review system behaviour, retailer behaviour, and supplier behaviour, where agent-based modelling is applied to model customer and online review system behaviours while system dynamics is used to model supplier and retailer behaviours (i.e. APIOBPCS). Compared with previous studies in this field, the novelty of the simulation models in this thesis is that they simultaneously consider online reviews and supply chain operations (especially inventory management in the supply chain) in different configurations, covering necessary customer heterogeneity and supply chain nonlinearities. This essentially enhances the generalisation of mathematical models. Table 7.2 below summarises the heterogeneities and nonlinearities considered in the simulation which are also visualised in Figure 7.1 using green and blue dots, respectively.
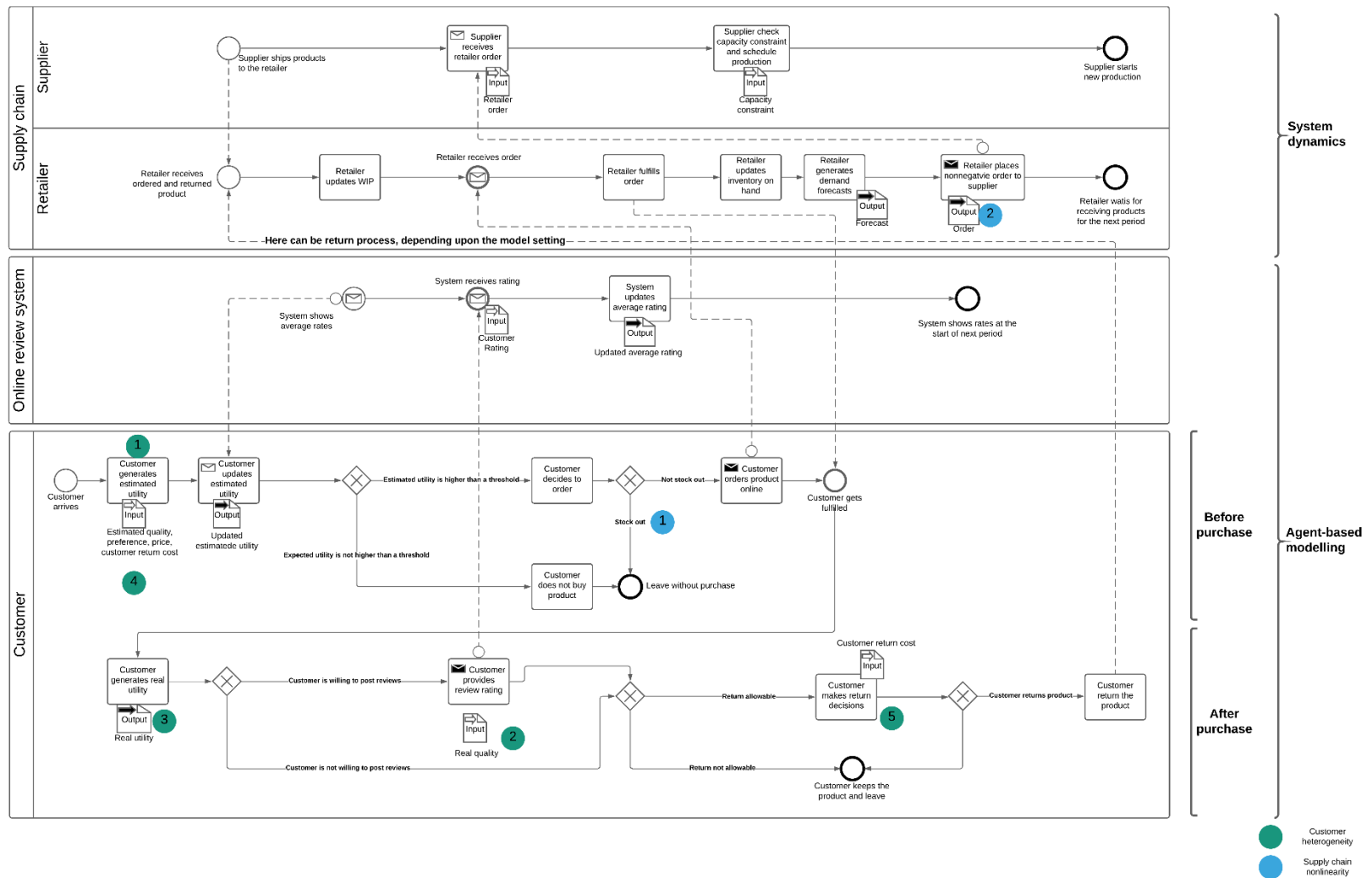
Figure 7.1 Process description of modelling framework in this thesis

Customer heterogeneity (green in Figure 7.1)	Modelling approach
1. Customer heterogenous preference	Uniform distribution
2. Customer heterogenous ex-post quality experience	Uniform distribution
3. Different customer review posting willingness	Bernoulli distribution
4. Purchase decision considering customer return cost M	Equation 6.4 in Chapter 6 which is implemented by numerical integration in RStudio
5. Customer heterogenous return processes	Equation 6.9 in Chapter 6 with piecewise function
Supply chain nonlinearity (blue in Figure 7.1)	Modelling approach
1. Customer sales lost when they are unfulfilled	The fulfilled demand is not greater than the on-hand inventory plus newly arrived products
2. Orders of the retailer can be constrained by supplier capacity	Order O_t is less than capacity level

Table 7.2 Customer heterogeneity and supply chain nonlinearities in the models

Based on the general picture of simulation models, the OR-SCM can be presented to answer **RQ2**. As previous Chapters 3 to 6 covers OR-SCM from different aspects, here a summative answer synthesising each chapter is presented in Figure 7.2 which integrates models used in different supply chain configurations.

Before purchase

Estimated utility generation	1. Attributes based generation
	2. Distribution based generation
Review information interpretation and estimated utility update	1. Naïve interpretation (utility reflected in online reviews directly replaces estimated utility
	2. Weighted average interpretation
	3. Bayeisan update
Purchase decision	1. Updated estimated utility is greater than 0
	2. Updated estimated utility is greater than a threshold
Ordering behaviour	1. Order and wait to fulfill
	2. Order but leave if stock-out occurs

After purchase

Real utility generation	1. Distribution based generation
	2. Attributes based generation
Behaviour of rating	1. All customers rate
	2. Probabilistic rating decision
	3. Rating-utility based rating decision
Value of rating	1. Naïve rating (rating is equal to realised quality)
	2. Utility based rating
	3. Distribution based rating
Product return	1. Utility based return
	2. Probabilistic return
	3. No return

Online review system

Format of rating	1. Real number (which can even be negative)
	2. Real number with only limited decimal points (1- or 2-digits) retained
Update procedures of rating	1. Calculating average value for all previously posted ratings
	2. Calulating average value for posted ratings in a specific time window
Quality of rating	1. All ratings are real
	2. Rating with real and fake (promotional) rating

Customers

Retailer

Inventory control	1. No inventory control
	2. Inventory control (e.g. order-up-to policy)
	3. Inventory control with reverse logistics
Competition	1. No competition
	2. Two or more retailers competing
	3. Competiting itself(multi-channel)
Pricing	1. Price taker
	2. Optimal pricing

Supplier

Capacity of production	1. Unlimited
	2. Capacitated
Deficits of items	1. Equal quality for every item
	2. Occasional defective items
Sourcing	1. Single sourcing
	2. Daul sourcing
Pricing	1. Price taker
	2. Optimal pricing

Figure 7.2 Summative description of OR-SCM framework

Specifically, this framework has three layers, with the top layer indicated as the letters in red (i.e {B, A, O, R, S}) and the second layer as the letters in purple. For example, for Customer (before purchase), there are four clusters in the second layer, namely {B [E, R, P, O]}. The bottom layer (i.e. level 3) consists of the specific activities which need to be modelled and the different ways to model them. For example, for Real utility generation in Customer (after purchase) cluster, there are two ways to model it, namely attribute-based generation and distribution based generation, and they are expressed by the subscript of second-layer clusters, for example $[R_1, R_2]$. The detailed description of each activity and corresponding modelling approaches are listed in Appendix A2.

The framework outlines the most important parts that need to be modelled and different approaches that previous research used. Therefore, it can be used to describe studies in this field. For example, for the Chapter 4, the framework-based description is {B[E_1, R_1, P_1, O_2],

A[R_2, B_2, V_1, P_3], O[F_1, U_1, Q_1], R[I_2, C_1], S[C_1, Q_1, S_1]}. For Chapter 5, the description is {B[E_1, R_1, P_1, O_2], A[R_2, B_2, V_1, P_3], O[F_1, U_1, Q_1], R[I_2, C_1], S[C_2, Q_1, S_1]}. For the seminal work by Kwark et al. (2014), it can be expressed as {B[E_1, $R_{2\&3}$, P_1, O_1], A[P_3], O[F_1, Q_1], R[I_1, C_1], S[C_1, Q_1, S_2]}. It can be seen that there are some elements in the second layer that are missing while other elements may contain multiple items from level 3. This is because in Kwark et al. (2014), the authors consider the steady state of online reviews without modelling rating behaviour of customers after purchase. They do not use any variations of the APIOBPCS model, but this framework can still manage to describe it, indicating its flexibility. Based on this framework, some very interesting topics can be explored, which are discussed in Section 7.5.1.

The flexibility of this framework should be noticed and the building blocks can work as a norm to direct future research. Supported by the rich variation of supply chain structures (see Lin et al. (2017) for a review) as well as multiple types of customer heterogeneity (in this thesis, only preference, quality and return heterogeneity is considered), more studies with practical values can be developed based on this framework.

RQ3. How does the influence of adopting online reviews differ between supply chain configurations?

Answer: **RQ3** concerns the different influences of online reviews between supply chain configurations. In Chapters 4 to 6, the influence of online reviews is examined in an uncapacitated forward supply chain, capacitated forward supply chain, and a closed-loop supply chain, respectively. Consistent with the current research stream (Table 2.4), the influences studied in the three chapters are considered from a connecting-tool mechanism perspective. In other words, three models all investigate how online reviews can influence supply chain performance through considering online review's enhancement of communication efficiency and effectiveness in the supply chain.

Note:
1. **Adopt** here means it is highly likely adopting online reviews is better than not adopting online reviews, while **No** here means it is highly likely not adopting online reviews is better than adopting them.
2. *CapCon*: capacity constraints; *ReC*: reverse supply chain cost; *M*: customer return cost.
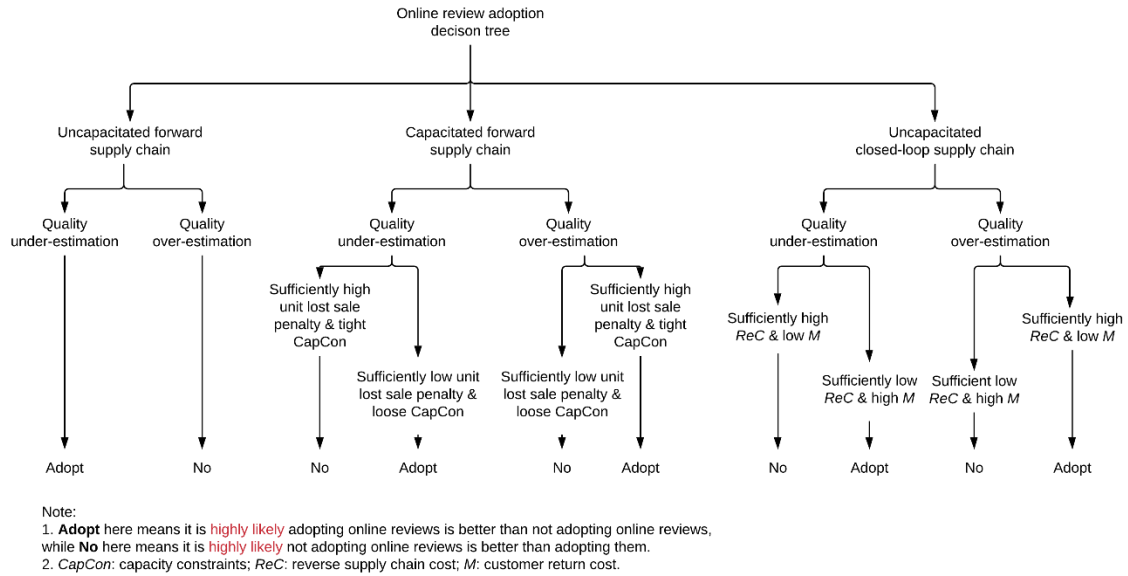
Figure 7.3 Decision tree for online review adoption

To synthesise the different influences between supply chain configurations as well as to inform companies about their decisions on online review adoption, a decision tree is provided in Figure 7.3. This decision tree simplifies the results from Chapters 4 to 6 and summarises the situations when companies should adopt or not adopt online reviews. It can be observed in Figure 7.3 that some of the situations are not included, such as the 'high lost sale penalty but loose constraint' in the capacitated supply chain. This is because for those situations not included, companies cannot easily decide whether adopting online reviews are superior and they need to analyse this decision based on different contexts.

The realisation of the connecting-tool mechanism in Chapters 4 to 6 all starts from modelling how customer estimated utility can be influenced by the online review information. In these models, without checking rating information in online review system, the customers will form biased quality estimation and thus biased estimated utility on the product, indicating the customers are not fully informed. However, through online reviews, previous customers can 'communicate' with prospective customers and deliver the information about the real quality of the product through product rating, in which way the estimation bias of prospective customer can be mitigated, and the rational estimation (but not always necessarily accurate expectation as demonstrated in Chapter 6) can be formed. Based on the new estimation, customers will change their purchase behaviours which eventually influence the supply chain performance. In

Chapters 4 to 6, such realisation of the connecting-tool mechanism is the same. However, when the results of the three chapters are compared, it can be observed that the influence of online reviews differs between supply chain configurations. Here, the comparison of the difference is discussed below.

First, using supply chain profitability as a performance measure, Chapter 4 shows the main way in which online reviews influence the supply chain performance is mainly to change the sales and consequently revenue of the supply chain. Specifically, when customers under-estimate product quality, adopting online reviews can correct customer estimation bias and lead to demand increase. The increased demand caused by online review adoption then brings more sales and revenue and eventually lead to higher profit. Conversely, when customers over-estimate product quality, adopting online reviews can correct customer over-estimation bias and thus decrease the demand. The reduction in the demand therefore leads to lower revenue and eventually profit loss. Also, the results indicate the supply lead time can also moderate the influence of online reviews on supply chain profitability, but such moderation effect looks much less strong than quality estimation. It should be noticed that not only revenue is influence by online review adoption under different customer estimation bias, but also the total holding cost and total lost sale penalty. However, simulation results show that the change in both costs (i.e. total holding cost and total lost sale penalty) induced by online review adoption produces a less significant impact on the profitability compared with the change of revenue.

When extending the model to the capacitated supply chain configuration in Chapter 5, the influence of online reviews on profitability shows some difference from Chapter 4. Specifically, the results demonstrate that the influence of online review adoption comes mainly from its effects on changing revenue and lost sale penalty. When customers have under-estimation bias, online review adoptions correct their bias and induce higher product demand. The consequences of this effect can lead to more fulfilled orders if the capacity constraint is loose, or bring more lost sales if the constraint is tight. More fulfilled orders generate higher revenue while more lost sales lead to higher costs (especially when the level of the unit lost sale penalty is high), and the overall profit is essentially determined by the difference between revenue and lost sale penalty. When customers have over-estimation bias, the causal relationship is exactly opposite to the under-estimation case, but the supply chain profitability is still mainly

determined by the relative change of total revenue and total lost sale penalty. The results demonstrate the complexity of online review adoption. Compared with Chapter 4, the quality estimation is not the only factor that moderates the online review influence on supply chain performance, as the results are also moderated by two more factors (unit lost sale penalty level and capacity constraint level).

Finally, when product return is considered in the system, Chapter 6 reveals the online adoption decisions mainly influence two important values which are the total revenue and total reverse supply chain cost, and the relative change due to online review adoption between total revenue and total reverse supply chain cost dominantly determines the supply chain profitability. Although there are other costs including the total holding cost and lost sale penalty, the influence from them brings negligible contribution to supply chain profitability. Specifically, the influence of online review adoption on total revenue and reverse supply chain cost works as follows. When customers have under-estimation bias, using online reviews can correct their bias and bring higher demand and thus sales. Meanwhile, it also leads to higher product return which increases the cost in the reverse supply chain. If the unit reverse supply chain cost (i.e. ReC) is low, the extra profit obtained from online review adoption will not diminish, eventually leading to higher profit. Otherwise, the extra profit is not able to compensate the increase in total cost in the reverse supply chain once the ReC is quite high and thus leads to profit loss. When over-estimation bias exists, the supply chain profitability is still mainly influenced by the difference between total revenue and total cost of the reverse supply chain, but the casual relationship is exactly the opposite to the under-estimation case. What is more interesting is that Chapter 6 finds redefining the quality under-estimation and quality over-estimation can better facilitate the explanation of the influence of online reviews on supply chain performance. Specifically, the quality under-estimation is redefined as the situation where 'the quality estimated by customers without online reviews is lower than the quality reflected in online reviews in system steady state' while the over-estimation is defined as the opposite. Such modified definition does not post any change on Chapters 4 and 5 but is more inclusive for Chapter 6 as it manages to consider the effect from rating probability difference.

Figure 7.1, 7.2, and 7.3 essentially summarised all the formulations and results of mathematical simulations. Also, a hierarchical relationship can be observed from three figures: Figure 7.2

directs the development of Figure 7.1, while the simulation results from the application of Figure 7.1 leads to the generation of Figure 7.3. The author believes that three figures are tightly connected with each other, and they can significantly contribute to research and practice as a whole. From the perspective of reserach, interested researchers can use Figure 7.2 as a basis to extend the structures of Figure 7.1 and generates new scenarios of online review adoption, which can verify or extend the results of Figure 7.3. Specifically, some of the feasible and promising research directions are discussed in the following section. From the perspective of practice, Figure 7.1 to 7.3 can work as a decision support system to inform the practitioners' decision making on online review adoption under different supply chain configurations. For example, managers can adopt the framework proposed in these figures to design their online review response strategy while policy makers can be informed to design new policies to protect online customers' welfare. In the following section, the practical implications will be discussed in detail.

What needs to be emphasised again is that this thesis focuses on the B2C transaction. Therefore, the results as well as the managerial insights generated from the thesis studies can be primarily generalisable to the B2C E-commerce supply chain. Also, the 'products' modelled in this thesis fall into the category of 'experienced goods' (Kuksov and Xie, 2010; Li and Hitt, 2010) in which case the quality of the products cannot be fully inspected by the customers and the complete quality information can only be obtained after buying and using the products. In practice, the products studied in the models can be the fast fashing goods (e.g. clothes), consumer electronics, and books sold online. In other words, the products modelled in this thesis are unlikely to be repetitively bought by the customers, otherwise the customers have full knowledge about the product quality and the information of quality conveyed in the online reviews is of little use for the customers.

7.3 Thesis contribution

This thesis studied the influence of online review adoption on supply chain performance. By considering different types of online review functions and different supply chain activities, this thesis summarised the generic mechanisms explaining how adopting online reviews can influence supply chain performance. This thesis then examined how such influence differs

between supply chain configurations through a systemic perspective using hybrid simulation modelling. The simulation models built in this thesis also stimulate the development of a modelling framework called OR-SCM which integrates online reviews to supply chain modelling. According to the thorough review of previous literature, what this thesis has done contributes to the important directions receiving little focus from previous studies, and thus the author believes this thesis has both research and practical contributions. Table 7.3 summarised these contributions.

Summary of contributions	
Research contribution	*Topic contribution* 1. This thesis proposed the mechanisms to explain the influence of online reviews on supply chain performance from a systemic perspective. 2. This thesis identified different variables that can moderate the influence of online reviews on supply chain performance. 3. This thesis considered inventory management in the supply chain with online reviews. 4. This thesis considered the capacitated supply chain configuration and closed-loop supply chain configuration. *Methodological contribution* 1. This thesis proposed an OR-SCM framework to link inventory management to online review modelling in supply chain. 2. This thesis developed hybrid simulation models in R for studying online reviews in supply chain.
Practical contribution	1. This thesis raised the awareness of the complexity of online review adoption to the managers from a supply chain management perspective. 2. This thesis suggested the possible conflicts between supply chain managers and marketing managers on online review adoption. 3. This thesis provided evidence to the policy makers to develop policies to regulate the possible online review manipulation and to protect customer welfare.

Table 7.3 Summary of research and practical contributions

For research contributions, this thesis is believed to contribute to topics as well as methodologies. As the literature review shows that, although there are increasing studies focusing on the influence of online reviews in the supply chain, none of them proposes a generic mechanism to explain the influence of online reviews on supply chain performance

from a systemic perspective. Therefore, the connecting-tool mechanism and data-source mechanism proposed in this thesis are good systemic explanations for the influence of online reviews in the supply chain and provide a theoretic basis for future work related to this topic. Apart from the mechanisms proposed, this thesis also contributes to extending the focus on the influence of online reviews to the capacitated supply chain and closed-loop supply chain which are important topics but not covered by previous research. The comparison of the influence of online review between supply chain configurations reflects the complexity of online review adoption, and raises the awareness to the researchers that the adoption decision is contingent on different contextual factors. This enhances the understanding of the value of online reviews in different supply chain configurations and paves the way for future studies.

For the methodological contributions, this thesis contributes to the use of hybrid simulation in this field through developing an OR-SCM framework. From Chapter 2, it can be identified that only a few papers in this field adopt mathematical modelling methods, with simulations being rarely used (i.e. only 1 paper). However, the discussion on analytical methods in Chapter 3 demonstrates that analytical methods have to simplify some of the important assumptions on supply chain nonlinearities and customer heterogeneities. Due to these shortcomings, the use of simulation makes the model more realistic and generalisable, as it is a powerful tool to integrate nonlinearity, dynamics, and heterogeneity in the model. Therefore, the framework built in this thesis can work as guidance for future modelling studies. Also, this thesis uses R (RStudio) to develop the hybrid simulation model. To the best of the author's knowledge, this thesis is the first to use R to link agent-based modelling and system dynamics (i.e. APIOBPCS) to study the influence of online reviews on supply chain performance. As the excellence for simulation and statistical analysis shown by R in this thesis, the author believes the way of using R to implement the whole model can enrich the methodological choice for future research on this topic.

Turning to practical contributions, this thesis enhances the understanding of the practical value of online reviews in the supply chain, and informs companies and managers to make better decisions on adopting online reviews. The mechanisms posted in Chapter 2 demonstrate that online reviews are not only an information and communication tool to convey customer feedback, but also an invaluable source for data analysis and supply chain process improvement,

especially with the aid of the rapidly developed big data technologies. Therefore, to make the most of online reviews, supply chain managers should consider the value of online reviews for both communication and data analysis and make their investment and training decisions accordingly.

The results of simulation modelling can also inform managers about online review adoption choices (as Figure 7.3 shows). The results of Chapters 4 to 6 indicate that if customers are consistently incorrectly estimating quality, then the use of reviews can have significant impact. Sometimes, such an impact is negative to the profitability. Therefore, supply chain managers should keep abreast of trends in online review scores to ensure that any changing trends in these are identified as soon as possible to enable a response. Also, as noted earlier, counter-intuitive results occur where under-estimating quality may lead to profit increases. Such a situation may create conflict between supply chain and marketing managers, and therefore it is important for businesses to understand what trade-offs exist. There are reputational risks for firms in effectively under-selling their products which could detract customers from considering a purchase in the first place.

By shedding light on how companies can strategically use online reviews to make more profit, this may lead to practices which are harmful to customers. Therefore, policy makers may then seek to introduce relevant policies could be built to protect customers. For example, the UK's Competitions and Markets Authority (2016) already publishes guidelines for firms on the use of online reviews. If firms become selective in how they use online reviews, then they may be in breach of these regulations. There may also be opportunities for similar guidelines to be introduced elsewhere. However, challenges remain in how these may be enforced.

7.4 Limitations

Online review research in the supply chain is still in its infancy. Although this thesis contributes to extend the boundary of the research in this field in several directions, the author acknowledges here are still limitations of this thesis, which also provides opportunities for future research.

First, in the model, only one retailer and one supplier are considered in the market. However, in the practice, the number of retailers and suppliers can be different. As summarised in Figure 2.6 in Chapter 2, for example, there can be the case that a supply chain having one supplier but two competing retailers. Also, it can be possible for one retailer to apply a dual sourcing strategy where two suppliers provide products for the retailer. The change of the supply chain structure can make the influence of online review adoption more diverse.

Also, this thesis assumes all online reviews are real, which means every customer gives an honest opinion in the reviews that they post. However, this is not always the case. It is possible that reviews are strategically manipulated, including promotional or fake reviews posted by companies to attract customers and lead to higher customer demand (Dellarocas, 2006; Mayzlin et al., 2014). Also, from the results in Chapters 5 and 6, it can be equally possible that companies can benefit from posting bad reviews as suggested from simulation results.

Moreover, this thesis only uses supply chain profitability to evaluate the performance, which means it evaluates the online review value from a company perspective. However, some authors argued that online review value should also be evaluated from a customer perspective to check how online review adoption can bring customer surplus and welfare (e.g. Li and Hitt, 2008; Zhang et al., 2017). Also, this thesis does not consider the influence of online reviews on the supply chain operational performance such as bullwhip effect or fill rate (e.g. Cannella et al., 2008).

Finally, only the steady state performance of the system (i.e. supply chain plus online reviews system) is considered. Although such measure is consistent with the approach adopted in previous studies (e.g. Kwark et al., 2014; Cai et al., 2018, Li et al. 2019b), the transient response effect of the system is not considered. If the product life cycle is relatively long, steady state measure will bring little influence, but it may generate biased insights if the product life cycle is short as it can be possible that the product is out of the market before the online review rating and supply chain system have converged to the true quality.

7.5 Future research opportunities

In this section, future research opportunities are provided. Specifically, the opportunities are group into topic extensions which can be explored based on the framework built by this thesis, and the method extensions for which can be explored using other modelling and analysis techniques. A brief summary is presented in Table 7.4.

	This thesis	**Future directions**
Topic extension	Single sourcing	Dual sourcing
	No retailer competition	Competing retailers
	Real rating	Manipulated rating
	Price taker	Optimal pricing under online review adoption
	Profitability as performance measure	Customer welfare, bullwhip effect or fill rate as performance measure
Method extension	Steady state simulation	Transient period analysis
	APIOBPCS	Newsvendor model or EOQ

Table 7.4 Future directions by topics and methods

7.5.1 Topic extensions

Although this thesis modelled and simulated three general types of the supply chain, there are other types of supply chain structures and activities commonly observed in practice. In addition, the performance measure in this thesis only considers profitability without including other measures (e.g. customer welfare, bullwhip effect, fill rate, etc.). Therefore, four potential topic extensions are provided for future research.

7.5.1.1 Dual Sourcing

One of the extensions is the dual sourcing supply chain which sees a common retailer sourcing products from two suppliers. Previous studies suggest sourcing products from two or multiple

suppliers can mitigate the disadvantages of the single source, such as instability supply (Wang et al., 2010) or supply constraints (Zhang et al., 2012).

Although previous literature discusses many aspects of the dual sourcing problem, such as the cost, lead time, and capacity of different suppliers, future research can focus on the product quality of different suppliers from the perspective of online review adoption in the supply chain. More specifically, future studies can consider the retailer's decision-making on online review adoption when facing two suppliers who supply a single type of products with different quality levels. The problems of different supply quality have been explored in some research (e.g. Liu et al., 2004; Wagner et al., 2019), but not from an online review perspective. Therefore, it is promising for future research to investigate the interaction between online review adoption and product quality difference as well as the percentage of orders placed to each supplier.

7.5.1.2 Retailer competition

Apart from the dual sourcing supply chain, the supply chain structure can be more complicated by considering retailer competition. A simple and straightforward extension can be made based on Li and Hitt (2010) and Kwark et al. (2014), where two competing retailers, namely retailer 1 and retailer 2, are assumed in the market, selling product 1 and product 2 which are assumed as imperfect substitutes. Extending their models, future research can add supply side modelling. Based on this thesis, the equations of the supply chain in the base model can be directly applied to this competition model without any change. By doing this, the extended model adds supply chain elements in competition under the influence of online reviews and can consider the behaviours that customers compare different products. What is more promising is that the extension can examine the influence of product stock-outs on customer switching behaviour.

7.5.1.3 Online review manipulation

In this thesis, online reviews are assumed real, and customers give an honest opinion in what they post. However, this is not always the case. It is possible that reviews are strategically manipulated, including promotional or fake reviews posted by companies to attract customers (Dellarocas, 2006; Mayzlin et al., 2014). To add online review manipulation behaviour to the model built in this thesis, future research can consider two types of customers, namely 'normal'

customers and 'recruited' customers. Normal customers are the customers in the thesis model, but the recruited customers are paid by companies to generate good reviews for the product. Normal customers make purchase decisions based on their estimated utility (i.e. U_{it}^e), while recruited customers will always purchase the product if there is no stock-out condition. After purchasing and getting fulfilled, normal customers will post their rating based on their real quality realized, while recruited customers will always post a good review. As there is no need to consider the utility of recruited customers before and after purchase, this model essentially only focuses on normal customers. Compared with what has been done in this thesis, the model formulation for online review manipulation is otherwise unchanged, as only the online review process is affected. Future research can focus on the behaviour of companies in online review manipulation to inform policy making and protect customer welfare.

7.5.1.4 Pricing decisions under online review adoption considering perceived quality

The models developed in this thesis only considered the situation where the players of supply chain are price takers, consistent with the previous literature (e.g. Minnema et al., 2016; Sahoo et al., 2018). However, such assumption essentially ignores the pricing behaviour of the retailer as well as the supplier. Some of the previous literature suggested that the pricing behaviour in the supply chain under online review adoption can be complicated due to the different quality estimation even without considering the influence from inventory management (e.g. Kwark et al, 2014; Sun and Xu, 2018). Therefore, if future study extends the work in this thesis, it is an interesting direction to investigate the pricing decisions of the retailer and the supplier under the adoption of online reviews and different quality estimation with inventory management considered.

It should be noticed that because of the nonlinearity and heterogeneity of the supply chain decisions, the objective function is highly likely to be non-convex. Therefore, if future research tends to optimise the price of different players in the supply chain, numerical methods like heuristics may be necessary.

7.5.1.5 Alternative performance measure

This thesis only uses supply chain profitability to evaluate the performance, which means the

evaluation of the online review influence is from a company perspective. However, online review value could be evaluated from customer perspective to check online review influence on customer surplus and welfare (Li and Hitt, 2008; Zhang et al., 2018), as well as the influence on supply chain operational performance including bullwhip, inventory variance amplification or fill rate (Cannella et al., 2008). Therefore, an interesting extension can be creating a compound performance indicator combining multiple decision criteria to evaluate the influence of online reviews in the supply chain.

7.5.2 Method extension

Although the proposed framework in this thesis shows its flexibility in modelling different types of the supply chain, there can be other techniques suiting this topic. This section lists three possible method extensions for future research.

7.5.2.1 Transient analysis

In this thesis, the models developed only considered the performance of steady state system. Although this thesis is consistent with previous research like Kwark et al. (2014), Li et al. (2019b), and Cai et al. (2018), it poses the gap for exploring transient system performance from the online review influence perspective. As it is also very common to see that online reviews are also applied to many short life cycle products such as some fresh foods which are only sold in one season, extension to include the transient analysis is very promising and has practical value. Under this setting, the online review rating is not necessarily convergent to the true quality before the end of the life cycle, which means the way to model and analyse the performance should be altered. One possible way to extend the methods used in this thesis to the transient analysis is to use different statistical tools, which can be found in Law (2015). Also, some techniques to measure transient performance can be borrowed from control engineering (Nise, 2020).

7.5.2.2 Newsvendor and online reviews

Followed by the previous transient analysis extension, another direction is the combination of newsvendor and online reviews, which may provide an alternative option to fill the gap to study the effect of transient state effect. To fit the logic of newsvendor, the model needs to be

assumed as (at least) two periods. Adapted from Chapters 4 to 6, the estimated quality for customers in the first period is exogenously generated as there is no customer posting online reviews yet. After that, the second-period customer estimated quality updates to the real quality as online review rating converges to it. As demand is determined by the estimated quality which is directly affect by online review ratings, if the online reviews are adopted, the demand distributions of two periods are thus different. Future studies can analyse the ordering policy of the company and compare the difference between adopting and not adopting online reviews from a newsvendor perspective.

7.5.2.3 Continuous review system extension

Contrary to the periodic review system, continuous system (i.e. (R,Q) system) is another commonly studied topic and it is very succinct in its analytical form. As it shares some similar properties with the discrete system, it is possible to examine online review influence on the supply chain from a continuous review system perspective. For example, it is promising to study what kind of impact will be brought on re-ordering point and fill rate from adopting online reviews.

7.6 Chapter summary

This chapter summarises the whole thesis and answers each research question. The thesis contribution and implications are drawn, and the limitations and possible future directions are discussed from multiple perspectives. To conclude, although this thesis explores the online review influence on the supply chain from several different angles, there are still many gaps to be filled in the future. As this area starts attracting research attention, the author would believe that in the following years there will be more studies on it.

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Appendix

A1. R codes for Chapters 4 to 6

Chapter 4:

```r
library(Rlab)

## Rlab 2.15.1 attached.

##
## Attaching package: 'Rlab'

## The following objects are masked from 'package:stats':
##
##      dexp, dgamma, dweibull, pexp, pgamma, pweibull, qexp, qgamma,
##      qweibull, rexp, rgamma, rweibull

## The following object is masked from 'package:datasets':
##
##      precip

library(car)

## Warning: package 'car' was built under R version 3.6.1

## Loading required package: carData

#sim_1_fun is for the situation when online reviews are not adopted
sim_1_fun <- function(Tp,prior_belief){

  simlength <- 20000
  #Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  products_price <- 1
  alpha <- 0.2 #
```

```r
product_cost <- 0.7
holding_cost <- 0.0045
lost_cost <- 0.35

Titlename <- matrix(NA, nrow = 1, ncol = 9)
simulationSC <- matrix(0,nrow = Tp+simlength, ncol=9)
Titlename[1,1] <- "Time"
Titlename[1,2] <- "Customer"
Titlename[1,3] <- "Demand"
Titlename[1,4] <- "Fulfilled_demand"
Titlename[1,5] <- "Rating"
Titlename[1,6] <- "Forecasting"
Titlename[1,7] <- "Inventory"
Titlename[1,8] <- "Work_in_process"
Titlename[1,9] <- "Order"
colnames(simulationSC) <- Titlename

#generate time periods
for(i in 1:(length(simulationSC[,1]))){
  simulationSC[i,1] <- i-Tp
}

#generate customer arrivals
for(i in 1:(length(simulationSC[,2]))){
  simulationSC[i,2] <- customer_numbers
}

#initial inventory is set as 100
for(i in 1:Tp){
  simulationSC[i,7] <- 100
}

#initial condition
```

```r
    simulationSC[(Tp+1),3] <- length(which((prior_belief+runif(custome
r_numbers,0,1)-products_price)>0))
    simulationSC[(Tp+1),4] <- min(simulationSC[Tp,7],simulationSC[(Tp+
1),3])
    simulationSC[(Tp+1),7] <- max(0,simulationSC[Tp,7]-simulationSC[(T
p+1),3])
    simulationSC[(Tp+1),6] <- simulationSC[(Tp+1),3]#naive forecasting
 for the first period
    simulationSC[(Tp+1),8] <- 0
    simulationSC[(Tp+1),9] <- round(max(0,(Tp+2)*simulationSC[(Tp+1),6
]-simulationSC[(Tp+1),7]-simulationSC[(Tp+1),8]))

  for(i in (Tp+2):(Tp+simlength)){
    simulationSC[i,3] <- length(which((prior_belief+runif(customer_n
umbers,0,1)-products_price)>0))
    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9]-simulationSC[i,3],0)
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),9]
-simulationSC[(i-Tp-1),9]
    simulationSC[i,9] <- round(max(0,(Tp+2)*simulationSC[i,6]-simula
tionSC[i,7]-simulationSC[i,8]))
  }

  output_table <- array(NA,5)
  output_table[1] <- sum((products_price-product_cost)*simulationSC[
3004:(simlength+Tp),4])#revenue minues production cost
  output_table[2] <- sum(holding_cost*(simulationSC[3004:(simlength+
Tp),7]))#holding cost
  output_table[3] <- sum(lost_cost*(simulationSC[3004:(simlength+Tp)
```

```r
,3]-simulationSC[3004:(simlength+Tp),4]))#lost_sale cost
  output_table[4] <- output_table[1]-output_table[2]-output_table[3]
#profit
  output_table[5] <- length(which(simulationSC[3004:(simlength+Tp),9
]>0))

  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5]))
}


#sim_2_fun is the situation when online reviews are adopted

sim_2_fun <- function(Tp,prior_belief){

  simlength <- 20000+1
  #Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  products_price <- 1
  alpha <- 0.2 #
  proba_review <- 0.1

  product_cost <- 0.7
  holding_cost <- 0.0045
  lost_cost <- 0.35

  Titlename <- matrix(NA, nrow = 1, ncol = 9)
  simulationSC <- matrix(0,nrow = Tp+simlength, ncol=9)
  Titlename[1,1] <- "Time"
  Titlename[1,2] <- "Customer"
  Titlename[1,3] <- "Demand"
  Titlename[1,4] <- "Fulfilled_demand"
  Titlename[1,5] <- "Rating"
```

```r
Titlename[1,6] <- "Forecasting"
Titlename[1,7] <- "Inventory"
Titlename[1,8] <- "Work_in_process"
Titlename[1,9] <- "Order"
colnames(simulationSC) <- Titlename

for(i in 1:(length(simulationSC[,1]))){
  simulationSC[i,1] <- i-Tp
}

for(i in (Tp+1):(length(simulationSC[,2]))){
  simulationSC[i,2] <- customer_numbers
}

#initial inventory is set as 100
for(i in 1:Tp){
  simulationSC[i,7] <- 100
}

#intial review is set as -999
simulationSC[,5] <- -999

#agent based modeling
  agent_matrix <- matrix(NA,nrow = simlength*50, ncol = 7)
  colnames(agent_matrix) <- c("ID","pri_belief","search_x","purchase
_decision",
                             "post_exp","post_decisions","online_ra
ting")
  for(i in 1:(simlength*50)){agent_matrix[i,1] = i}

  #initial condition
  for(i in 1:50){
    agent_matrix[i,2]=prior_belief #pri_belief
```

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```r
    agent_matrix[i,3]=runif(1,0,1) #search x
    agent_matrix[i,4]=agent_matrix[i,2]+agent_matrix[i,3]-products_p
rice # utility (pri)
    if(agent_matrix[i,4]>0){
      agent_matrix[i,5]=runif(1,0,1) #post quality
      agent_matrix[i,6]=rbern(1,proba_review) #post decisions
      agent_matrix[i,7]=agent_matrix[i,5] #rating
    } else {
      agent_matrix[i,5:7] = -999
    }
  }

  agent_rating <- matrix(-999,nrow=simlength*50,ncol=2)
  colnames(agent_rating) <- c("customer_posted","online_rating")
  for(i in 1:length(agent_rating[,1])){agent_rating[i,1]=i}

  simulationSC[(Tp+1),3] <- length(which((agent_matrix[1:50,4])>0))
  simulationSC[(Tp+1),4] <- min(simulationSC[Tp,7],simulationSC[(Tp+
1),3])
  simulationSC[(Tp+1),7] <- max(0,simulationSC[Tp,7]-simulationSC[(T
p+1),3])
  if(simulationSC[(Tp+1),4]==0){
    simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
  } else {
    if(length(which(agent_matrix[1:50,6]==1))==0){
      simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
    } else {
      p_dem_fulfilled <- agent_matrix[1:50,7][which(agent_matrix[1:5
0,4]>0)][1:simulationSC[(Tp+1),4]]
      p_quo <- agent_matrix[1:50,6][which(agent_matrix[1:50,4]>0)][1
:simulationSC[(Tp+1),4]]
      if(length(which(p_quo==1))==0){
        simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
```

```r
      } else {
        p_post_review <- which(p_quo==1)
        p_number <- length(p_dem_fulfilled[p_post_review])
        agent_rating[1:p_number,2] <- p_dem_fulfilled[p_post_review]
        simulationSC[(Tp+2),5] <- mean(agent_rating[which(agent_rati
ng[,2]>=0),2])
      }
    }
  }
  simulationSC[(Tp+1),6] <- simulationSC[(Tp+1),3]#naive forecasting
 for the first period
  simulationSC[(Tp+1),8] <- 0
  simulationSC[(Tp+1),9] <- round(max(0,(Tp+2)*simulationSC[(Tp+1),6
]-simulationSC[(Tp+1),7]-simulationSC[(Tp+1),8]))

  for(i in (Tp+2):(Tp+simlength-1)){
    for(k in ((i-Tp-1)*50+1):((i-Tp-1)*50+50)){
      agent_matrix[k,2]=ifelse(simulationSC[i,5]<0,prior_belief,simu
lationSC[i,5])
      agent_matrix[k,3]=runif(1,0,1)
      agent_matrix[k,4]=agent_matrix[k,2]+agent_matrix[k,3]-products
_price
      if(agent_matrix[k,4]>0){
        agent_matrix[k,5]=runif(1,0,1)
        agent_matrix[k,6]=rbern(1,proba_review)
        agent_matrix[k,7]=agent_matrix[k,5]
      } else {
        agent_matrix[k,5:7]=-999
      }
    }
    simulationSC[i,3] <- length(which(agent_matrix[((i-Tp-1)*50+1):(
(i-Tp-1)*50+50),4]>0))
    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
```

```r
p-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9]-simulationSC[i,3],0)
    if(simulationSC[i,4]==0){
      simulationSC[(i+1),5] <- simulationSC[i,5]
    } else {
      if (length(which(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50)
,6]==1))==0){
        simulationSC[(i+1),5] <- simulationSC[i,5]
      } else {
        p_d_f <- agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),7][wh
ich(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),4]>0)][1:simulatio
nSC[i,4]]
        p_q <- agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),6][whic
h(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),4]>0)][1:simulationS
C[i,4]]
        if(length(which(p_q==1))==0){
          simulationSC[(i+1),5] <- simulationSC[i,5]
        } else {
          p_post <- which(p_q==1)
          p_n <- length(p_d_f[p_post])

          agent_rating[((i-Tp-1)*50+1):((i-Tp-1)*50+p_n),2] <- p_d_f
[p_post]
          simulationSC[(i+1),5] <- mean(agent_rating[which(agent_rat
ing[,2]>=0),2])
        }
      }
    }
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),9]
-simulationSC[(i-Tp-1),9]
```

```r
      simulationSC[i,9] <- round(max(0,(Tp+2)*simulationSC[i,6]-simula
tionSC[i,7]-simulationSC[i,8]))


  }
  output_table <- array(NA,5)
  output_table[1] <- sum((products_price-product_cost)*(simulationSC
[3004:(simlength+Tp-1),4]))#revenue-pro cost
  output_table[2] <- sum(holding_cost*simulationSC[3004:(simlength+T
p-1),7])
  output_table[3] <- sum(lost_cost*(simulationSC[3004:(simlength+Tp-
1),3]-simulationSC[3004:(simlength+Tp-1),4]))
  output_table[4] <- output_table[1]-output_table[2]-output_table[3]
  output_table[5] <- length(which(simulationSC[3004:(simlength+Tp-1)
,9]>0))


  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5]))
}
```

Chapter 5

```r
library(Rlab)
```

```
## Rlab 2.15.1 attached.

##
## Attaching package: 'Rlab'

## The following objects are masked from 'package:stats':
##
##      dexp, dgamma, dweibull, pexp, pgamma, pweibull, qexp, qgamma,
##      qweibull, rexp, rgamma, rweibull

## The following object is masked from 'package:datasets':
##
##      precip
```

```r
library(car)
```

```
## Warning: package 'car' was built under R version 3.6.1

## Loading required package: carData
```

```r
#sim_1_fun is for the situation when online reviews are not adopted
sim_1_fun <- function(cap_con,lost_cost,prior_belief){

  simlength <- 20000
  Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  products_price <- 1
  alpha <- 0.2 #

  product_cost <- 0.7
  holding_cost <- 0.0045
  #lost_cost <- 0 #0.35; 0.7
```

```r
  #cap_tight <- 1.25#1.5;100
  #cap_con <- 25#10 25 40 with the lowest capacity lower than the average of under-estimation and higest one higher than the over-estimation

  Titlename <- matrix(NA, nrow = 1, ncol = 9)
  simulationSC <- matrix(0,nrow = Tp+simlength, ncol=9)
  Titlename[1,1] <- "Time"
  Titlename[1,2] <- "Customer"
  Titlename[1,3] <- "Demand"
  Titlename[1,4] <- "Fulfilled_demand"
  Titlename[1,5] <- "Rating"
  Titlename[1,6] <- "Forecasting"
  Titlename[1,7] <- "Inventory"
  Titlename[1,8] <- "Work_in_process"
  Titlename[1,9] <- "Order"
  colnames(simulationSC) <- Titlename

  #generate time periods
  for(i in 1:(length(simulationSC[,1]))){
    simulationSC[i,1] <- i-Tp
  }

  #generate customer arrivals
  for(i in 1:(length(simulationSC[,2]))){
    simulationSC[i,2] <- customer_numbers
  }

  #initial inventory is set as 100
  for(i in 1:Tp){
    simulationSC[i,7] <- 100
  }
```

```r
  #initial condition
  simulationSC[(Tp+1),3] <- length(which((prior_belief+runif(custome
r_numbers,0,1)-products_price)>0))
  simulationSC[(Tp+1),4] <- min(simulationSC[Tp,7],simulationSC[(Tp+
1),3])
  simulationSC[(Tp+1),7] <- max(0,simulationSC[Tp,7]-simulationSC[(T
p+1),3])
  simulationSC[(Tp+1),6] <- simulationSC[(Tp+1),3]#naive forecasting
 for the first period
  simulationSC[(Tp+1),8] <- 0
  simulationSC[(Tp+1),9] <- round(min(cap_con,max(0,(Tp+2)*simulatio
nSC[(Tp+1),6]-simulationSC[(Tp+1),7]-simulationSC[(Tp+1),8])))

  for(i in (Tp+2):(Tp+simlength)){
    simulationSC[i,3] <- length(which((prior_belief+runif(customer_n
umbers,0,1)-products_price)>0))
    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9]-simulationSC[i,3],0)
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),9]
-simulationSC[(i-Tp-1),9]
    simulationSC[i,9] <- round(min(cap_con,max(0,(Tp+2)*simulationSC
[i,6]-simulationSC[i,7]-simulationSC[i,8])))
  }

  output_table <- array(NA,5)
  output_table[1] <- sum((products_price-product_cost)*simulationSC[
3004:(simlength+Tp),4])#revenue minues production cost
  output_table[2] <- sum(holding_cost*(simulationSC[3004:(simlength+
```

```r
Tp),7]))#holding cost
  output_table[3] <- sum(lost_cost*(simulationSC[3004:(simlength+Tp)
,3]-simulationSC[3004:(simlength+Tp),4]))#lost_sale cost
  output_table[4] <- output_table[1]-output_table[2]-output_table[3]
#profit
  output_table[5] <- length(which(simulationSC[3004:(simlength+Tp),9
]>0))

  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5]))
}


#sim_2_fun is for online review adoption

sim_2_fun <- function(cap_con,lost_cost,prior_belief){

  simlength <- 20000+1
  Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  products_price <- 1
  alpha <- 0.2 #
  proba_review <- 0.1

  product_cost <- 0.7
  holding_cost <- 0.0045
  #lost_cost <- 0 #0.35; 0.7

  #cap_tight <- 1.25#1.5;100
  #cap_con <- 25


  Titlename <- matrix(NA, nrow = 1, ncol = 9)
```

```r
  simulationSC <- matrix(0,nrow = Tp+simlength, ncol=9)
  Titlename[1,1] <- "Time"
  Titlename[1,2] <- "Customer"
  Titlename[1,3] <- "Demand"
  Titlename[1,4] <- "Fulfilled_demand"
  Titlename[1,5] <- "Rating"
  Titlename[1,6] <- "Forecasting"
  Titlename[1,7] <- "Inventory"
  Titlename[1,8] <- "Work_in_process"
  Titlename[1,9] <- "Order"
  colnames(simulationSC) <- Titlename


  for(i in 1:(length(simulationSC[,1]))){
    simulationSC[i,1] <- i-Tp
  }


  for(i in (Tp+1):(length(simulationSC[,2]))){
    simulationSC[i,2] <- customer_numbers
  }


  #initial inventory is set as 100
  for(i in 1:Tp){
    simulationSC[i,7] <- 100
  }


  #intial review is set as -999
  simulationSC[,5] <- -999

#agent based modeling
  agent_matrix <- matrix(NA,nrow = simlength*50, ncol = 7)
  colnames(agent_matrix) <- c("ID","pri_belief","search_x","purchase
_decision",
                             "post_exp","post_decisions","online_ra
```

```
ting")
  for(i in 1:(simlength*50)){agent_matrix[i,1] = i}

  #initial condition
  for(i in 1:50){
    agent_matrix[i,2]=prior_belief #pri_belief
    agent_matrix[i,3]=runif(1,0,1) #search x
    agent_matrix[i,4]=agent_matrix[i,2]+agent_matrix[i,3]-products_p
rice # utility (pri)
    if(agent_matrix[i,4]>0){
      agent_matrix[i,5]=runif(1,0,1) #post quality
      agent_matrix[i,6]=rbern(1,proba_review) #post decisions
      agent_matrix[i,7]=agent_matrix[i,5] #rating
    } else {
      agent_matrix[i,5:7] = -999
    }
  }

  agent_rating <- matrix(-999,nrow=simlength*50,ncol=2)
  colnames(agent_rating) <- c("customer_posted","online_rating")
  for(i in 1:length(agent_rating[,1])){agent_rating[i,1]=i}

  simulationSC[(Tp+1),3] <- length(which((agent_matrix[1:50,4])>0))
  simulationSC[(Tp+1),4] <- min(simulationSC[Tp,7],simulationSC[(Tp+
1),3])
  simulationSC[(Tp+1),7] <- max(0,simulationSC[Tp,7]-simulationSC[(T
p+1),3])
  if(simulationSC[(Tp+1),4]==0){
    simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
  } else {
    if(length(which(agent_matrix[1:50,6]==1))==0){
      simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
    } else {
```

```r
      p_dem_fulfilled <- agent_matrix[1:50,7][which(agent_matrix[1:5
0,4]>0)][1:simulationSC[(Tp+1),4]]
      p_quo <- agent_matrix[1:50,6][which(agent_matrix[1:50,4]>0)][1
:simulationSC[(Tp+1),4]]
      if(length(which(p_quo==1))==0){
        simulationSC[(Tp+2),5] <- simulationSC[(Tp+1),5]
      } else {
        p_post_review <- which(p_quo==1)
        p_number <- length(p_dem_fulfilled[p_post_review])
        agent_rating[1:p_number,2] <- p_dem_fulfilled[p_post_review]
        simulationSC[(Tp+2),5] <- mean(agent_rating[which(agent_rati
ng[,2]>=0),2])
      }
    }
  }
  simulationSC[(Tp+1),6] <- simulationSC[(Tp+1),3]#naive forecasting
 for the first period
  simulationSC[(Tp+1),8] <- 0
  simulationSC[(Tp+1),9] <- round(min(cap_con,max(0,(Tp+2)*simulatio
nSC[(Tp+1),6]-simulationSC[(Tp+1),7]-simulationSC[(Tp+1),8])))

  for(i in (Tp+2):(Tp+simlength-1)){
    for(k in ((i-Tp-1)*50+1):((i-Tp-1)*50+50)){
      agent_matrix[k,2]=ifelse(simulationSC[i,5]<0,prior_belief,simu
lationSC[i,5])
      agent_matrix[k,3]=runif(1,0,1)
      agent_matrix[k,4]=agent_matrix[k,2]+agent_matrix[k,3]-products
_price
      if(agent_matrix[k,4]>0){
        agent_matrix[k,5]=runif(1,0,1)
        agent_matrix[k,6]=rbern(1,proba_review)
        agent_matrix[k,7]=agent_matrix[k,5]
      } else {
```

```r
        agent_matrix[k,5:7]=-999
      }
    }
    simulationSC[i,3] <- length(which(agent_matrix[((i-Tp-1)*50+1):(
(i-Tp-1)*50+50),4]>0))
    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),9]-simulationSC[i,3],0)
    if(simulationSC[i,4]==0){
      simulationSC[(i+1),5] <- simulationSC[i,5]
    } else {
      if (length(which(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50)
,6]==1))==0){
        simulationSC[(i+1),5] <- simulationSC[i,5]
      } else {
        p_d_f <- agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),7][wh
ich(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),4]>0)][1:simulatio
nSC[i,4]]
        p_q <- agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),6][whic
h(agent_matrix[((i-Tp-1)*50+1):((i-Tp-1)*50+50),4]>0)][1:simulationS
C[i,4]]
        if(length(which(p_q==1))==0){
          simulationSC[(i+1),5] <- simulationSC[i,5]
        } else {
          p_post <- which(p_q==1)
          p_n <- length(p_d_f[p_post])

          agent_rating[((i-Tp-1)*50+1):((i-Tp-1)*50+p_n),2] <- p_d_f
[p_post]
          simulationSC[(i+1),5] <- mean(agent_rating[which(agent_rat
ing[,2]>=0),2])
        }
```

```r
      }
    }
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),9]
-simulationSC[(i-Tp-1),9]
    simulationSC[i,9] <- round(min(cap_con,max(0,(Tp+2)*simulationSC
[i,6]-simulationSC[i,7]-simulationSC[i,8])))

  }
  output_table <- array(NA,5)
  output_table[1] <- sum((products_price-product_cost)*(simulationSC
[3004:(simlength+Tp-1),4]))#revenue-pro cost
  output_table[2] <- sum(holding_cost*simulationSC[3004:(simlength+T
p-1),7])
  output_table[3] <- sum(lost_cost*(simulationSC[3004:(simlength+Tp-
1),3]-simulationSC[3004:(simlength+Tp-1),4]))
  output_table[4] <- output_table[1]-output_table[2]-output_table[3]
  output_table[5] <- length(which(simulationSC[3004:(simlength+Tp-1)
,9]>0))

  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5]))
}
```

Chapter 6

```r
library(Rlab)

## Rlab 2.15.1 attached.

##
## Attaching package: 'Rlab'

## The following objects are masked from 'package:stats':
##
##     dexp, dgamma, dweibull, pexp, pgamma, pweibull, qexp, qgamma,
##     qweibull, rexp, rgamma, rweibull

## The following object is masked from 'package:datasets':
##
##     precip

library(car)

## Warning: package 'car' was built under R version 3.6.1

## Loading required package: carData

#sim_1_fun is for the situation without online reviews
sim_1_fun <- function(q_estimate,RSCO,return_cost){

  simlength <- 20000
  Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  price <- 1
  alpha <- 0.2 #

  product_cost <- 0.7
  holding_cost <- 0.0045
  lost_cost <- 0.35
```

```r
  #RSCO <- 0.6 this is the ReC value in the thesis

  #q_estimate <- 0.7
  product_sigma <- 0.2
  #return_cost <- 0.15#this is the M in the thesis, with its value equal to 0.01,0.15,0.3

  q_real <- 0.5


  #purchase decision function is equation (6.5) which is numerically
 cross-checked by using equation (6.7)
  #cp:customer preference;pp:product price;rc:cost for sending product back
  purchase_decision <- function(cp,u) {
    test_1 <- function(x) (x+cp-price)*(1/(product_sigma*sqrt(2*pi)))*exp(-(((x-u)/product_sigma)^2)/2)
    p1=integrate(test_1, lower = price-cp-return_cost, upper = Inf)
    result_1=p1$value*(1-pnorm(price-cp-return_cost,mean=u,sd=product_sigma))+pnorm(price-cp-return_cost,mean=u,sd=product_sigma)*(-return_cost)
    if (result_1>0){
      return (1)
    } else {
      return (0)
    }
  }
  #------------------------------------------------------------------------------------------

  Titlename <- matrix(NA, nrow = 1, ncol = 11)
  simulationSC <- matrix(0,nrow = Tp+simlength+1, ncol=11)
  Titlename[1,1] <- "Time"
```

```r
    Titlename[1,2] <- "Customer"
    Titlename[1,3] <- "Demand"
    Titlename[1,4] <- "Fulfilled_demand"
    Titlename[1,5] <- "Rating"
    Titlename[1,6] <- "Forecasting"
    Titlename[1,7] <- "Inventory"
    Titlename[1,8] <- "WIP"
    Titlename[1,9] <- "return"
    Titlename[1,10] <- "Re_WIP"
    Titlename[1,11] <- "Order"
    colnames(simulationSC) <- Titlename

    #generate time periods
    for(i in 1:(length(simulationSC[,1]))){
      simulationSC[i,1] <- i-Tp-1
      simulationSC[i,5] <- -Inf
    }

    #generate customer arrivals
    for(i in (Tp+2):(length(simulationSC[,2]))){
      simulationSC[i,2] <- customer_numbers
    }

    #initial inventory is set as 100 (a relatively large inventory)
    for(i in 1:(Tp+1)){
      simulationSC[i,7] <- 100
    }

  preference_matrix <- matrix(0, nrow = customer_numbers*(length(sim
ulationSC[,3])-(Tp+1)), ncol = 6)
    colnames(preference_matrix) <- c("customer_no","preference_xi","pu
rchase_or_not","fulfilled_or_not","realised_q","return_decisions")
    for(i in 1:(length(preference_matrix[,1]))){
```

```r
    preference_matrix[i,1] <- i
    preference_matrix[i,2] <- runif(1,0,1)
    preference_matrix[i,3] <- purchase_decision(preference_matrix[i,
2],q_estimate)
    preference_matrix[i,5] <- rnorm(1,q_real,product_sigma)
  }


  for(i in 1:(length(simulationSC[,3])-(Tp+1))){
    simulationSC[(i+Tp+1),3] <- sum(preference_matrix[(50*(i-1)+1):(
50*i),3])
  }

  #initial condition

  simulationSC[(Tp+2),4] <- min(simulationSC[(Tp+1),7],simulationSC[
(Tp+2),3])
  simulationSC[(Tp+2),7] <- max(0,simulationSC[(Tp+1),7]-simulationS
C[(Tp+2),3])
  simulationSC[(Tp+2),6] <- simulationSC[(Tp+2),3]#naive forecasting
 for the first period
  simulationSC[(Tp+2),8] <- 0

  if (simulationSC[(Tp+2),4]==0){
    simulationSC[(Tp+2),9] = 0
  } else {
    if (length(which(preference_matrix[1:50,3]==1))==0){
      simulationSC[(Tp+2),9] = 0
    } else {
      c1 <- which(preference_matrix[1:50,3]==1)[1:simulationSC[(Tp+2
),4]]
      preference_matrix[c1,4] <- 1
```

```r
    for(i in 1:50){
      if (preference_matrix[i,4]==1){
        if (preference_matrix[i,5]+preference_matrix[i,2]-price+re
turn_cost<0){
          preference_matrix[i,6] = 1
        } else {
          preference_matrix[i,6] = 0
        }
      } else {
        preference_matrix[i,6] = 0
      }
    }
    simulationSC[(Tp+2),9] <- sum(preference_matrix[1:50,6])
  }
}

  simulationSC[(Tp+2),10] <- 0
  simulationSC[(Tp+2),11] <- round(max(0,(Tp+2)*simulationSC[(Tp+2),
6]-simulationSC[(Tp+2-Tp-1),9]-simulationSC[(Tp+2),7]-simulationSC[(
Tp+2),8]-simulationSC[(Tp+2),10]))

  #the second to the last

  for(i in (Tp+3):(Tp+simlength+1)){
    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),11]+simulationSC[(i-Tp-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),11]+simulationSC[(i-Tp-1),9]-simulationSC[i,3],0)
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),11
]-simulationSC[(i-Tp-1),11]
```

```r
    if (simulationSC[i,4]==0){
      simulationSC[i,9] = 0
    } else {
      if (length(which(preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(T
p+2)+1)),3]==1))==0){
        simulationSC[i,9] = 0
      } else {
        cw <- which(preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(Tp+2
)+1)),3]==1)[1:simulationSC[i,4]]

        preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(Tp+1))),4][cw] <
- 1

        for(j in (50*(i-Tp-2)+1):(50*(i-Tp-1))){
          if (preference_matrix[j,4]==1){
            if (preference_matrix[j,5]+preference_matrix[j,2]-price+
return_cost<0){
              preference_matrix[j,6] = 1
            } else {
              preference_matrix[j,6] = 0
            }
          } else {
            preference_matrix[j,6] = 0
          }
        }
        simulationSC[i,9] <- sum(preference_matrix[(50*(i-Tp-2)+1):(
50*(i-Tp-1)),6])
      }
    }

    simulationSC[i,10] <- simulationSC[(i-1),10]+simulationSC[(i-1),
9]-simulationSC[(i-Tp-1),9]
    simulationSC[i,11] <- round(max(0,(Tp+2)*simulationSC[i,6]-simul
ationSC[(i-Tp-1),9]-simulationSC[i,7]-simulationSC[i,8]-simulationSC
```

```r
[i,10]))
  }

  output_table <- array(NA,9)
  output_table[1] <- sum(simulationSC[3005:(simlength+Tp),11])
  output_table[2] <- sum(simulationSC[3005:(simlength+Tp),7])
  output_table[3] <- sum(simulationSC[3005:(simlength+Tp),3]-simulat
ionSC[3005:(simlength+Tp),4])
  output_table[4] <- sum(simulationSC[3005:(simlength+Tp),9])
  output_table[5] <- price*sum(simulationSC[3005:(simlength+Tp),4]-s
imulationSC[3005:(simlength+Tp),9])-product_cost*output_table[1]-hol
ding_cost*output_table[2]-lost_cost*output_table[3]-RSCO*output_tabl
e[4]
  output_table[6] <- -Inf
  output_table[7] <- mean(simulationSC[3005:(simlength+Tp),7])
  output_table[8] <- mean(simulationSC[4005:(simlength+Tp),7])
  output_table[9] <- mean(simulationSC[5005:(simlength+Tp),7])
  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5],output_table[6],output_table[7],output_table[
8],output_table[9]))
}

#sim_2_fun is for online reviews adopted

sim_2_fun <- function(q_estimate,RSCO,return_cost,prob_rating){

  simlength <- 20000+1 #changes are made here
  Tp <- 3
  customer_numbers <- 50
  #prior_belief <- 0.3 # 0.5; 0.7
  price <- 1
  alpha <- 0.2 #
```

```r
  product_cost <- 0.7
  holding_cost <- 0.0045
  lost_cost <- 0.35

  #prob_rating <- 0.74#0.48
  #q_estimate <- 0.7
  product_sigma <- 0.2


  #RSCO <- 0.3
  q_real <- 0.5

  #purchase decision function (equation (6.5) cross-checked using eq
uation (6.7))
  #cp:customer preference;pp:product price;rc:cost for sending produ
ct back
  purchase_decision <- function(cp,u) {
    test_1 <- function(x) (x+cp-price)*(1/(product_sigma*sqrt(2*pi))
)*exp(-(((x-u)/product_sigma)^2)/2)
    p1=integrate(test_1, lower = price-cp-return_cost, upper = Inf)
    result_1=p1$value*(1-pnorm(price-cp-return_cost,mean=u,sd=produc
t_sigma))+pnorm(price-cp-return_cost,mean=u,sd=product_sigma)*(-retu
rn_cost)
    if (result_1>0){
      return (1)
    } else {
      return (0)
    }
  }


  #------------------------------------------------------------
--------------
```

```r
Titlename <- matrix(NA, nrow = 1, ncol = 11)
simulationSC <- matrix(0,nrow = Tp+simlength+1, ncol=11)
Titlename[1,1] <- "Time"
Titlename[1,2] <- "Customer"
Titlename[1,3] <- "Demand"
Titlename[1,4] <- "Fulfilled_demand"
Titlename[1,5] <- "Rating"
Titlename[1,6] <- "Forecasting"
Titlename[1,7] <- "Inventory"
Titlename[1,8] <- "WIP"
Titlename[1,9] <- "return"
Titlename[1,10] <- "Re_WIP"
Titlename[1,11] <- "Order"
colnames(simulationSC) <- Titlename

#generate time periods
for(i in 1:(length(simulationSC[,1]))){
  simulationSC[i,1] <- i-Tp-1
  simulationSC[i,5] <- -Inf
}

#generate customer arrivals
for(i in (Tp+2):(length(simulationSC[,2]))){
  simulationSC[i,2] <- customer_numbers
}

#initial inventory is set as 100 (a relatively large inventory)
for(i in 1:(Tp+1)){
  simulationSC[i,7] <- 100
}

preference_matrix <- matrix(0, nrow = customer_numbers*(length(sim
ulationSC[,3])-(Tp+1)), ncol = 8)
```

```r
  colnames(preference_matrix) <- c("customer_no","preference_xi","pu
rchase_or_not","fulfilled_or_not","realised_q","return_decisions","r
ating_decisions","rate")

  for(i in 1:(length(preference_matrix[,1]))){
    preference_matrix[i,1] <- i
    preference_matrix[i,2] <- runif(1,0,1)
    preference_matrix[i,5] <- rnorm(1,q_real,product_sigma)
    preference_matrix[i,8] <- -Inf
  }

  #initial condition
  for(i in 1:50){
    preference_matrix[i,3] <- purchase_decision(preference_matrix[i,
2],q_estimate)
  }
  simulationSC[(Tp+2),3] <- sum(preference_matrix[1:50,3])

  simulationSC[(Tp+2),4] <- min(simulationSC[(Tp+1),7],simulationSC[
(Tp+2),3])
  simulationSC[(Tp+2),7] <- max(0,simulationSC[(Tp+1),7]-simulationS
C[(Tp+2),3])
  simulationSC[(Tp+2),6] <- simulationSC[(Tp+2),3]#naive forecasting
 for the first period
  simulationSC[(Tp+2),8] <- 0

  if (simulationSC[(Tp+2),4]==0){
    simulationSC[(Tp+2),9] = 0
  } else {
    if (length(which(preference_matrix[1:50,3]==1))==0){
      simulationSC[(Tp+2),9] = 0
    } else {
      c1 <- which(preference_matrix[1:50,3]==1)[1:simulationSC[(Tp+2
```

```r
),4]]
      preference_matrix[c1,4] <- 1

      for(i in 1:50){
        if (preference_matrix[i,4]==1){
          if (preference_matrix[i,5]+preference_matrix[i,2]-price+re
turn_cost<0){
            preference_matrix[i,6] = 1
          } else {
            preference_matrix[i,6] = 0
          }
        } else {
          preference_matrix[i,6] = 0
        }
      }
      simulationSC[(Tp+2),9] <- sum(preference_matrix[1:50,6])
    }
  }

  for(i in 1:50){
    if (preference_matrix[i,4]==1){
      if (preference_matrix[i,6]==1){
        preference_matrix[i,7] = 1
      } else {
        preference_matrix[i,7] = rbern(1,prob_rating)
      }
    } else {
      preference_matrix[i,7] = 0
    }

    if (preference_matrix[i,7]==1){
      preference_matrix[i,8] = preference_matrix[i,5]
    } else {
```

```r
      preference_matrix[i,8] = -Inf
    }
  }

  if (length(which(preference_matrix[1:50,8]==-Inf))==50){
    simulationSC[(Tp+2+1),5] <- -Inf
  } else {
    simulationSC[(Tp+2+1),5] <- mean(preference_matrix[1:50,8][which
(preference_matrix[1:50,8]>-Inf)])
  }

  simulationSC[(Tp+2),10] <- 0
  simulationSC[(Tp+2),11] <- round(max((Tp+2)*simulationSC[(Tp+2),6]
-simulationSC[(Tp+2-Tp-1),9]-simulationSC[(Tp+2),8]-simulationSC[(Tp
+2),7]-simulationSC[(Tp+2),10],0))

  #second to the last

  for(i in (Tp+3):(Tp+simlength)){
    for (j in (50*(i-Tp-2)+1):(50*(i-Tp-1))){
      if (simulationSC[i,5]==-Inf){
        preference_matrix[j,3] = purchase_decision(preference_matrix
[j,2],q_estimate)
      } else {
        preference_matrix[j,3] = purchase_decision(preference_matrix
[j,2],simulationSC[i,5])
      }
    }

    simulationSC[i,3] <- sum(preference_matrix[(50*(i-Tp-2)+1):(50*(
i-Tp-1)),3])

    simulationSC[i,4] <- min(simulationSC[(i-1),7]+simulationSC[(i-T
```

```r
p-1),11]+simulationSC[(i-Tp-1),9],simulationSC[i,3])
    simulationSC[i,7] <- max(simulationSC[(i-1),7]+simulationSC[(i-T
p-1),11]+simulationSC[(i-Tp-1),9]-simulationSC[i,3],0)
    simulationSC[i,6] <- alpha*simulationSC[i,3]+(1-alpha)*simulatio
nSC[(i-1),6]
    simulationSC[i,8] <- simulationSC[(i-1),8]+simulationSC[(i-1),11
]-simulationSC[(i-Tp-1),11]

  if (simulationSC[i,4]==0){
    simulationSC[i,9] = 0
    simulationSC[(i+1),5] = simulationSC[i,5]
  } else {
    if (length(which(preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(T
p+2)+1)),3]==1))==0){
      simulationSC[i,9] = 0
      simulationSC[(i+1),5] = simualtionSC[i,5]
    } else {
      cw <- which(preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(Tp+2
)+1)),3]==1)[1:simulationSC[i,4]]

      preference_matrix[(50*(i-(Tp+2))+1):(50*(i-(Tp+1))),4][cw] <
- 1
      for(k in (50*(i-Tp-2)+1):(50*(i-Tp-1))){
        if (preference_matrix[k,4]==1){
          if (preference_matrix[k,5]+preference_matrix[k,2]-price+
return_cost<0){
            preference_matrix[k,6] = 1
          } else {
            preference_matrix[k,6] = 0
          }
        } else {
          preference_matrix[k,6] = 0
        }
```

```
      }
      simulationSC[i,9] <- sum(preference_matrix[(50*(i-Tp-2)+1):(
50*(i-Tp-1)),6])


      for(u in (50*(i-Tp-2)+1):(50*(i-Tp-1))){
        if (preference_matrix[u,4]==1){
          if (preference_matrix[u,6]==1){
            preference_matrix[u,7] = 1
          } else {
            preference_matrix[u,7] = rbern(1,prob_rating)
          }
        } else {
          preference_matrix[u,7] = 0
        }

        if (preference_matrix[u,7]==1){
          preference_matrix[u,8] = preference_matrix[u,5]
        } else {
          preference_matrix[u,8] = -Inf
        }
      }


      if (length(which(preference_matrix[1:(50*(i-Tp-1)),8]>-Inf))
==0){
        simulationSC[(i+1),5] <- -Inf
      } else {
        simulationSC[(i+1),5] <- mean(preference_matrix[1:(50*(i-T
p-1)),8][which(preference_matrix[1:(50*(i-Tp-1)),8]>-Inf)])
      }
    }
  }
```

```r
    simulationSC[i,10] <- simulationSC[(i-1),10]+simulationSC[(i-1),
9]-simulationSC[(i-Tp-1),9]
    simulationSC[i,11] <- round(max(0,(Tp+2)*simulationSC[i,6]-simul
ationSC[(i-Tp-1),9]-simulationSC[i,7]-simulationSC[i,8]-simulationSC
[i,10]))
  }
  output_table <- array(NA,9)
  output_table[1] <- sum(simulationSC[3005:(simlength+Tp-1),11])
  output_table[2] <- sum(simulationSC[3005:(simlength+Tp-1),7])
  output_table[3] <- sum(simulationSC[3005:(simlength+Tp-1),3]-simul
ationSC[3005:(simlength+Tp-1),4])
  output_table[4] <- sum(simulationSC[3005:(simlength+Tp-1),9])
  output_table[5] <- price*sum(simulationSC[3005:(simlength+Tp-1),4]
-simulationSC[3005:(simlength+Tp-1),9])-product_cost*output_table[1]
-holding_cost*output_table[2]-lost_cost*output_table[3]-RSCO*output_
table[4]
  output_table[6] <- simulationSC[(simlength+Tp),5]#there is no '-1'
  output_table[7] <- mean(simulationSC[3005:(simlength+Tp-1),7])
  output_table[8] <- mean(simulationSC[4005:(simlength+Tp-1),7])
  output_table[9] <- mean(simulationSC[5005:(simlength+Tp-1),7])

  return(c(output_table[1],output_table[2],output_table[3],output_ta
ble[4],output_table[5],output_table[6],output_table[7],output_table[
8],output_table[9]))
}
#please pay attention: the whole process is simlength+1, so when mea
suring output, please
#minus one period as the lastest one contains just rating without ot
her data (i.e. inventory, demand, wip)
```

Components	Explanation	Representative reference
Customers: before purchase		
Estimated utility generation		
1. Attributes based generation	The utility is generated based on the value of different attributes, such as estimated product quality, customer preference and product price.	Hu et al. (2017); Li and Hitt (2008 & 2010); Jiang and Guo (2015)
2. Distribution based generation	The utility is directly generated from a pre-defined distribution, without considering any attribute.	Kuksov and Xie (2010)
Review information interpretation and estimated utility update		
1. Naïve interpretation	The utility reflected in online reviews is directly used to update estimated utility.	Li and Hitt (2008)
2. Weighted average interpretation	The updated expected utility is the weighted average between original estimated utility and the utility reflected in online reviews.	Jiang and Guo (2015); Kwark et al. (2014)
3. Bayesian update	The utility reflected in online reviews is used to update original estimated utility through Bayesian estimation.	Sohoo et al. (2018); Papanastasiou and Savva (2017)
Purchase decision		
1. Updated estimated utility is greater than 0	A customer will decide to purchase the product only if updated estimated utility is greater than 0.	Guan et al. (2020); Li and Hitt (2008)
2. Updated estimated utility is greater than a threshold	A customer will decide to purchase the product only if updated estimated utility is greater than a threshold.	Sohoo et al. (2018)
Ordering behaviour		
1. Order and wait to fulfil	Customer is modelled to order the product and wait until get fulfilled.	Dejonckheere et al. (2003)
2. Order but leave if stock out occurs	Customer is modelled to order the product only if the product is in stock.	Dominguez et al. (2018)
Customers: after purchase		
Real utility generation		

1. Distribution based utility	The real utility is generated from a pre-defined probability distribution, without specific attributes considered.	Kuksov and Xie (2010)
2. Attributes based utility	The real utility is generated from a group of attribute values.	Hu et al. (2017)

Behaviour of rating

1. All customers rate	Every customer will be modelled to rate the product.	Li and Hitt (2008 & 2010)
2. Probabilistic rating decision	Each customer has certain probability to rate the product.	Bhola and Hanna (2018)
3. Rating-utility based rating decision	Each customer will occur a rating utility and they will rate only this utility is greater than threshold.	Jiang and Guo (2015); Hu et al. (2018)

Value of rating

1. Naïve rating	Rating is modelled equal to the only one attribute (normally the product quality).	Li and Hitt (2008)
2. Rating subject to self-selection bias	Rating is modelled equal to the only one attribute but exposed to self-selection bias.	Hu et al. (2018)
3. Utility based rating	Rating is modelled equal to the post purchase utility.	Jiang and Guo (2015)
4. Distribution based rating	Rating is generated from a pre-defined distribution without considering any attribute.	Bhola and Hanna (2018)

Product return

1. Utility return	Return is based the real utility.	Sahoo et al. (2018)
2. Probabilistic return	Each customer has certain probability to return the product.	Minnema et al. (2016)

Online review system

Format of rating

1. Real number	The system will be modelled to show rating as real number without decimal points rounded.	Hu et al. (2017)
2. Real number with limited decimal points	The system will be modelled to show rounded ratings.	Jiang and Guo (2015); Huang et al. (2020)

Update procedures of rating

1. Calculating average value for all previous posted ratings	The rating shown in the system is the arithmetic mean of all previous posted ratings.	Jiang and Guo (2015); Li and Hitt (2008)
2. Calculating average value for posted previous ratings in a time window	The rating shown in the system is the arithmetic mean of ratings posted in a specific time window.	To be researched in the future research

Quality of rating

1. All ratings are real	All ratings are generated by customers to reflect the feedback they really want to deliver.	Sun (2012)
2. Ratings with real and fake ratings	Some of the ratings are manually manipulated.	Mayzlin (2006)

Retailer

Inventory control

1. No inventory control	No inventory control as well as supplier is considered in the model.	Li et al. (2019a & 2019b)
2. Heuristic inventory control	The safety stock level is equal to the one period forecasted demand.	Dejonckheere et al. (2003)
3. Control by optimising costs	The safety stock level is calculated by minimising the inventory-related cost (holding and backlog cost).	Dominguez et al. (2020)

Competition

1. No competition	Only one retailer is in the market.	Liu et al. (2019)
2. Two-or-more-retailer competition	More than one retailers are in the market.	Guo (2019)
3. Competing itself	Retailer has online and offline selling and it competes itself.	Yang et al. (in press);

Supplier

Capacity

1. Unlimited capacity	Supplier has unlimited production capacity.	Dejonckheere et al. (2003)
2. Capacitated	Supplier has capacity constraints.	Ponte et al. (2017b)

Quality of items

1. Equal quality of each item	Supplier produces homogenous product.	Dejonckheere et al. (2003)

2. Different quality for different item	The quality of each product can vary.	Liu et al. (2004); Wagner et al. (2019)

<u>Sourcing</u>

1. Single sourcing	Only one supplier is considered in the model.	Liu et al. (2019)
2. Dual sourcing (multi-sourcing)	More than one suppliers are considered in the model.	Kwark et al. (2014); Cai et al. (2018)

A3. Ethical approval and guidelines

Cardiff University ethical approval

Huang, Shupeng
Cardiff University Business School

08 October 2019

Dear Shupeng:

Ethics Approval Reference: E020191008
Project Title: Online review's influence on supply chain performance

I would like to confirm that your project has been granted ethics approval as it has met the review conditions.

Should there be a material change in the methods or circumstances of your project, you would in the first instance need to get in touch with us for re-consideration and further advice on the validity of the approval.

I wish you the best of luck on the completion of your research project.

Yours sincerely,

Electronic signature via email

Debbie Foster
Chair of the ethics sub-committee
Email: CARBSResearchOffice@cardiff.ac.uk

INFORM ethical guidelines website

https://www.informs.org/About-INFORMS/Governance/INFORMS-Ethics-Guidelines#:~:text=The%20Guidelines%20are%20available%20to,via%20operations%20research%20and%20analytics.

Notations for chapter 4 and 5	
q_{it}	Real product quality
x_{it}	Customer preference
p	Product price
θ	Forecasting smoothing parameters
N	Customers each period
q^e	Product quality estimation
L	Lead time (for forward supply chain)
$CapCon$	Capacity constraints
U_{it}	Real utility of customer i in period t
U_{it}^e	Estimated utility of customer i in period t
R_{it}	Rating posted by customer i in period t
$\bar{R}_t$	Average rating in period t
D_t	Customer demand in period t
D_t^*	Fulfilled customer demand in period t
O_t	Order placed by the retailer in period t
I_t	Inventory on hand of the retailer in the end of period t
WIP_t	Work-in-process in period t
F_t	Demand forecasting in period t

Notations for chapter 6	
q_μ	True mean product quality
σ_μ	Product quality standard deviation
x_{it}	Customer preference

p	Product price
M	Customer's product return cost
R_{it}	Rating posted by customer i in period t
$\bar{R}_t$	Average rating in period t
N	Number of customers
θ	Forecasting smoothing parameters
L	Lead time of forward supply chain
L_r	Lead time of reverse supply chain
q_μ^e	Mean value of quality estimation
ReC	Unit reverse supply chain cost
r_t	Remanufactured products
D_t	Customer demand in period t
D_t^*	Fulfilled customer demand in period t
O_t	Order placed by the retailer in period t
I_t	Inventory on hand of the retailer in the end of period t
WIP_t	Work-in-process in period t
F_t	Demand forecasting in period t