Abstract

The paper explores the influence of online review adoption on supply chain profitability under the presence of a capacity constraint. Nowadays, customers increasingly rely on online reviews for decision making, and online retailers regard reviews as a norm. Although online reviews have been extensively examined in marketing disciplines, little research has been conducted to investigate their influence from a supply chain perspective. In addition, previous research has largely focused on how online review information can influence customer purchase behaviours, but ignores the more basic decision: whether and when companies should adopt reviews. This paper examines the online review adoption decision from a capacitated supply chain perspective through mathematical modelling and simulation. The simulation considers the influence of variables including online review adoption decisions, capacity constraint level, lost sales penalty level and product quality estimation on supply chain profitability. Generally, we find that online reviews can bring more profit to the supply chain than without online reviews, although such influence is moderated by the other three variables. The findings reveal the complexity of the contextual variable impacts on online review adoption, and demonstrate that decisions concerning the adoption of online reviews should take all supply-chain-related variables into consideration rather than only aiming for increasing customer orders.

Keywords: Online reviews, supply chain, capacity constraint, simulation, inventory management.

The influence of online review adoption on the profitability of capacitated supply chain

1. Introduction

E-commerce has made a vast array of products and vendors available to the individual consumer, but with such extensive choice comes the question of whether a product will meet the expected quality of the purchaser. Whilst product descriptions typically have manufacturer-provided specifications to compare, many customers may struggle to envisage how these will suit their individual requirements. Instead, customers often turn to the experiences of prior purchasers of products to infer whether a given product or vendor is the best option for them. Online reviews are thus an invaluable source of information to support the purchasing decisions of customers, and may both substitute and complement other forms of word-of-mouth communication (Guo et al., 2020).

Within marketing disciplines there has been extensive research concerning the influence of online reviews on customer behaviour (Babić Rosario et al., 2016). Many studies focus on the value of online reviews in attracting new customers (Hu et al., 2008), clinching wavering customers (Hu et al., 2014), and affording price uplifts because of enhanced brand reputation (Öğüt and Onur Taş, 2012). From this perspective, online reviews can be exploited for the benefit of the sales function, generating revenue for the firm through orders placed by customers.

Whilst sales orders are usually welcome, firms do not survive and grow based on revenue; the key metric is profit. To be profitable it is crucial that order fulfilment is efficient and effective, and in practice this necessitates that the whole supply chain performs well. It is therefore notable that whilst there has been extensive research concerning online reviews in generating orders, only recently has there been limited exploration considering how these seemingly valuable information assets can be leveraged to support operations within the supply chain.

In this paper we therefore seek to show how the adoption of online reviews can affect the performance of supply chains, specifically those that are capacitated. We focus on inventory management within the supply chain which, from the perspective of cost efficiency and profitability, has been shown to be one of the most important facets of supply chain management research (Sterman, 1989). Given online reviews have been evidenced as making a significant contribution to the firm's revenue, and inventory management makes a key impact on supply chain profitability, it is notable that the unification of these important activities has almost entirely been overlooked by the research community.

One of the aspects that need exploration is how online reviews can influence inventory management when supply chain capacity is constrained. Nowadays, supply chains are more constrained by their capacities as the consequence of demand surges and cost increases in production and information technologies (Angelus and Zhu, 2017). Also, Gupta et al. (2021) suggest that disruptions to supply chains are occurring more frequently than before, leading to the loss of capacity. Literature suggests the influence of capacity constraints on the supply chain is complex and nonlinear, which not only limits the production volume but also increase the time of manufacturing (Costa et al., 2020). Supply chain performance is thus significantly impacted by supply chain capacity constraints (Cannella et al., 2018). As inventory management practices under capacity constraints can influence the supply chain efficiency and service level (Cannella et al., 2008), examining the online review influence on inventory management in a capacitated supply chain can enhance the understanding of online reviews in the supply chain management.

We approach this study using a combination of modelling and simulation. A model to depict a capacitated supply chain with online review influence is developed, along with factorial simulation experiments to analyse it. Using supply chain profit as the performance measure, our results show that the influence of online review adoption on capacitated supply chain performance is complicated and significantly moderated by other variables, including capacity constraint level, lost sales penalty level, and customer quality estimation. This paper makes three principal contributions:

- The influence of online reviews on inventory management is considered from a capacitated supply chain perspective for the first time.
- A novel simulation approach is developed by incorporating customer heterogeneity due to online reviews into a capacitated supply chain model.
- This paper raises awareness of complexity of online review adoption from a supply chain perspective.

This paper has six parts. After the introduction, Section 2 reviews the relevant literature including research on online reviews in supply chain and publications on supply chain capacity constraints. Section 3 develops the model and designs the simulation experiments. In Section 4, the results are analysed, followed by Section 5 where the mechanism of online review influence on the capacitated supply chain is discussed. Finally, Section 6 summarises the whole paper, including research contributions, model limitations, and future directions of pertinent study.

2. Literature review

Our paper is related to two streams of research. One is research on the influence of online reviews on supply chains, while the other is work about capacitated supply chains. In this section, we review each in turn.

2.1 Online reviews in supply chains

Research concerning online reviews in supply chains has gained considerable academic interest in recent years, and the influence of online reviews has been examined from multiple perspectives. Table 1 summarises the relevant research in different supply chain activities. One of the most popular topics identified is sales forecasting based on online reviews. Multiple features of online reviews are found to be effective predictors for future sales, such as average rating, review volume, review sentiment, review content, number of votes on helpfulness, number of questions answered etc. (Chong et al., 2017; Lau et al., 2018; Van Nguyen et al., 2020). Different methods are proposed, including linear regression and autoregression (See-To and Ngai, 2018), the Bass model (Fan et al., 2017), and advanced machine learning algorithms (Chong et al., 2017; Schneider and Gupta, 2016). Product-related attributes including new (Fan et al., 2017) and remanufactured products (Van Nguyen et al., 2020) are also considered.

Table 1. Relevant research summary by different supply chain operations

Supply chain operations	Relevant research	Method	
		Mathematical modelling	Empirical
Demand forecasting	Chong et al. (2017); Lau et al. (2018); Van Nguyen et al. (2020); See-To and Ngai (2018); Fan et al. (2017); Schneider and Gupta (2016).		✓
Physical product delivery	Hou et al. (2018).	✓	
Service delivery	Korfiatis et al. (2019); Sezgen et al. (2019); Lui et al. (2018); Su and Teng (2018); Jia (2020); Ko et al. (2019); James et al. (2017); Gu and Ye (2014).		✓
Product development	Zhang et al. (2019); Yang et al. (2019); Qi et al. (2016); Zhang et al. (2018); Chan et al. (2017); Liu et al. (2013); Jin et al. (2016).		✓
Return & reverse logistics	Minnema et al. (2016); Sahoo et al. (2018); Walsh and Möhring (2017).	✓	✓
Supply chain pricing	Li et al. (2019a); Liu et al. (2019); Cai et al. (2018).	✓	
Supply chain competition	Cai et al. (2018); Kwark et al. (2014).	✓	
Multi-channel supply chain	Li et al. (2019b); Yang et al. (2021).	✓	

In addition to research exploring demand forecasting, there has also been emphasis on the influence of online reviews in delivery. Interestingly, only a single paper relates to physical product delivery. In that study, Hou et al. (2018) investigated investment strategies and their outcomes for retailers in product delivery operations, comparing cases with and without online reviews. By comparison there has been much more research on the influence of online reviews in service delivery. One stream of such research uses content analysis or text mining techniques to extract information from online reviews and support the improvement of service delivery process. Multiple industries have been investigated, such as hospitality and tourism (e.g. Lui et al. 2018; Su and Teng, 2018; Jia, 2020), public transportation (Korfiatis et al., 2019; Sezgen et al., 2019), and healthcare (Ko et al., 2019; James et al., 2017). Additionally, online reviews have been used as a tool to facilitate service recovery as management responses can be made to customer complaints in reviews, improving service level and satisfaction (Gu and Ye, 2014).

Turning to product development, online review information is a good source of customer product evaluation, and companies can obtain customer preferences from analysing reviews to support product development and improvement (Zhang et al., 2019). Research has proposed methods for identifying customer opinions and preferences to achieve a customer-centred product design (Yang et al., 2019; Qi et al., 2016; Zhang et al., 2018). Among the papers different methods are proposed, ranging from qualitative analysis (Chan et al., 2017) to advanced text mining algorithms (Zhang et al., 2019; Liu et al., 2013; Jin et al., 2016).

Although research has mainly focused on the forward supply chain, there are also some studies on the reverse flow of products. Walsh and Möhring (2017) found that the presence of online reviews can decrease the rate of product returns compared with the absence of reviews. Of course, not all reviews are equal. Minnema et al. (2016) found review valence can significantly influence return probability, while review variance has limited influence on it. Furthermore, the integrity of the review is important too. Sahoo et al. (2018) found that unbiased reviews can contribute to lower return rates, while biased reviews with higher rating can increase the return probability as customers become disenchanted by products and services that fail to meet their online-review informed expectations.

Whilst most studies concerning online reviews employ empirical research methods such as content analysis and machine learning approaches, some adopt mathematical models to explore their influence. Compared with empirical papers that focus on a specific part of supply chain, mathematical modelling takes a more holistic view and investigates how online reviews influence the whole supply chain system. Such papers have covered topics in supply chain pricing and coordination strategy (Li et al., 2019a; Liu et al., 2019; Cai et al., 2018), multi-channel supply chain operations (Li et al., 2019b; Yang et al., 2021), and competition (Cai et al., 2018; Kwark et al., 2014). The influence of online reviews is frequently examined by comparing cases with and without online reviews.

The literature review suggests that although previous studies cover many facets of supply chain management, none of them clearly link online reviews to inventory management as well as supply chain capacity constraints. Addressing this gap, the current study explores the influence of online reviews on inventory management, in the context of capacitated supply chains.

2.2 Research on capacitated supply chains

Research on capacity constraints has been conducted for many years, through which multiple facets of constraint influence on supply chain management have been examined. We review the existing literature on supply chain capacity constraints from three dimensions, namely capacity constraint types in the model, dynamics of models, and supply chain performance measures. Table 2 presents the previous literature on supply chain capacity constraints categorised against each dimension, as well as including the positioning of this paper.

Table 2. Literature on supply chain capacity constraints

Literature	Capacity constraint types			Dynamics of the model		Supply chain performance measure	
	LO	LDLT	VC	Single period	Multi-period	Monetary measures	Operational measures
Zhao et al. (2002)	✓				✓	✓	✓
Georgiadis et al. (2006)	✓				✓	✓	
Vlachos et al. (2007)	✓				✓	✓	
Cannella et al. (2008)	✓				✓		✓
Lau et al. (2008)	✓				✓	✓	✓
Boute et al. (2009)		✓			✓	✓	
Shen et al. (2011)	✓				✓	✓	
Glock (2012)		✓			✓	✓	
Glock and Ries (2013)		✓			✓	✓	
Lin et al. (2014)	✓				✓		✓
Qi et al. (2015)	✓			✓		✓	
Angelus and Zhu (2017)	✓				✓	✓	
Ponte et al. (2017)	✓				✓		✓
Freeman et al. (2018)	✓			✓		✓	
Wu et al. (2018)	✓			✓		✓	
Cannella et al. (2018)		✓			✓		✓
Dominguez et al. (2019)	✓				✓		✓
Wang et al. (2019)	✓			✓		✓	
Costa et al. (2020)			✓		✓		✓
Gupta et al. (2021)			✓	✓		✓	
This paper	**✓**				**✓**	**✓**	

LO: Limiting Orders; LDLT: Load-Dependent Lead Time; VC: Variable Capacity

First, according to Cannella et al. (2018) and Costa et al. (2020), two general types of capacity constraint modelling are most commonly adopted in the previous literature, namely 'Limiting Orders' (LO) and 'Load-Dependent Lead Time' (LDLT). The LO approach models capacity constraints by arbitrarily adding a limitation to the number of orders, production volume, or transportation flows, while the LDLT approach models capacity constraints by assuming a higher volume of orders and production results in a longer system lead time.

For example, Ponte et al. (2017) adopted the LO approach to model capacity constraints, and they investigated the influence of capacity constraints on the bullwhip and fill rate of an order-up-to replenishment system with minimal-mean-square-error forecasting. They found that there exists a threshold value below which capacity constraints can have a significant impact on supply chain performance. Zhao et al. (2002) and Lau et al. (2008) also used the LO approach to investigate the influence of capacity constraints in supply chain cost efficiency. They defined a measure as 'capacity tightness' which is the ratio of capacity divided by demand. They found 'capacity tightness' can have a moderating effect on supply chain performance with other variables, such as information sharing and demand forecasting methods.

While LO approaches are the most common, some researchers have adopted the LDLT approach. For example, Glock and Ries (2013) studied an inventory system whose production lead time is a function of the lot size, and they found how both the number of suppliers and the delivery structure can influence the performance of the system. Cannella et al. (2018) modelled the capacity constraints of the supply chain as a dynamic and load-dependent value, and showed through mathematical simulation that capacity constraints can bring a negative influence on the supply chain system.

Beyond LO and LDLT, there are other approaches to capacity constraint modelling, such as Costa et al. (2020), who modelled the capacity as a function of changeovers between products in manufacturing and supply chain disruptions, and Gupta et al. (2021), who assumed capacity is influenced by supplier disruptions. Different from LO and LDLT approaches, these studies assumed the capacity constraints as a function of other events and therefore essentially variable constraints; we term this approach as 'variable capacity' (VC) models.

The second dimension considered is the dynamics of models, namely single-period models and multi-period models. Studies adopting single-period models usually conduct economic analyses in which game theories are used to explore the behaviours of different companies under the influence of capacity constraints. For example, Wu et al. (2018) proposed a two-echelon supply chain with downstream companies having capacity constraints. They developed information sharing mechanisms and pricing mechanisms for downstream companies. They also found the profits of the supply chain will be higher when capacity increases. Wang et al. (2019) studied a closed-loop supply chain with a supplier, a return product collector, and a capacitated manufacturer. Adopting a Stackelberg game, they found the optimal pricing and remanufacturing decisions for the supply chain.

Compared with single-period models, multi-period models focus on the influence of capacity constraints in a dynamic setting. For example, Dominguez et al. (2019) adopted a multi-period model and studied closed-loop supply chains where both forward and reverse supply chain have capacity limits. They found capacity constraints can relieve the bullwhip effects for both manufacturer and remanufacturer. Shen et al. (2011) considered the new product diffusion problem when the product supply is constrained, and analysed companies' optimal fulfilment and pricing policy.

Thirdly, the existing literature adopts different supply chain performance measures to evaluate the influence of capacity constraints on the system, and the measures can be generally categorised into monetary measures (e.g. cost and profit) and operational measures (e.g. customer service level, fill rate, bullwhip effect, inventory level, etc.). Many studies focus on the influence of capacity constraints on supply chain profitability or cost efficiency. For example, Freeman et al. (2018) investigated sourcing strategies to maximise the expected profit of a manufacturer who has capacity constraints and faces unreliable supply. Using stochastic programming, they found that the different capacity constraint levels lead to the change of optimal sourcing strategy choices. Georgiadis et al. (2006) and Vlachos et al. (2007) studied the influence of capacity constraints from the profitability perspective of the remanufacturing and closed-loop supply chain. Given that capacity can be built and expanded by companies, these papers used simulation to investigate the impact of alternative strategies for capacity planning under different situations.

Apart from monetary measures, supply chain operational performance is also researched from the capacity constraint perspective. Cannella et al. (2008) investigated the effect of capacity constraints on supply chain operational performance as well as how information sharing can affect this impact. In their study, demand amplification and service levels are used as the performance indicator to measure the influence generated from capacity constraint. Lin et al. (2014) explored the interaction between capacity constraints and customer baulking behaviour, finding that this can have a significant impact on bullwhip effect.

Therefore, based on the three dimensions, this paper can be positioned as a multi-period study adopting a LO approach and monetary supply chain performance measures. Where our work brings novelty is through the modelling approach for customer demand. In the previous models, customer demand is often assumed to follow general distributions such as normal distribution, Poisson distribution, or constant (e.g. Cannella et al., 2018; Ponte et al., 2017; Zhao et al., 2002; Cannella et al., 2008). However, we model the behaviour of each customer based on their utility from the product, with demand being derived from the aggregation of all customer behaviours. Our model then extends this approach to include the influence of online reviews. This approach embraces the interactions between customers and online review system, therefore better capturing the influence of online reviews on the supply chain performance.

3. Model development

In this paper, a capacitated e-commerce supply chain with online reviews is modelled. The model consists of two parts: demand generation and supply. A pictorial description for our model is presented in Figure 1 to compare when this supply chain adopts online reviews and when it does not adopt them.

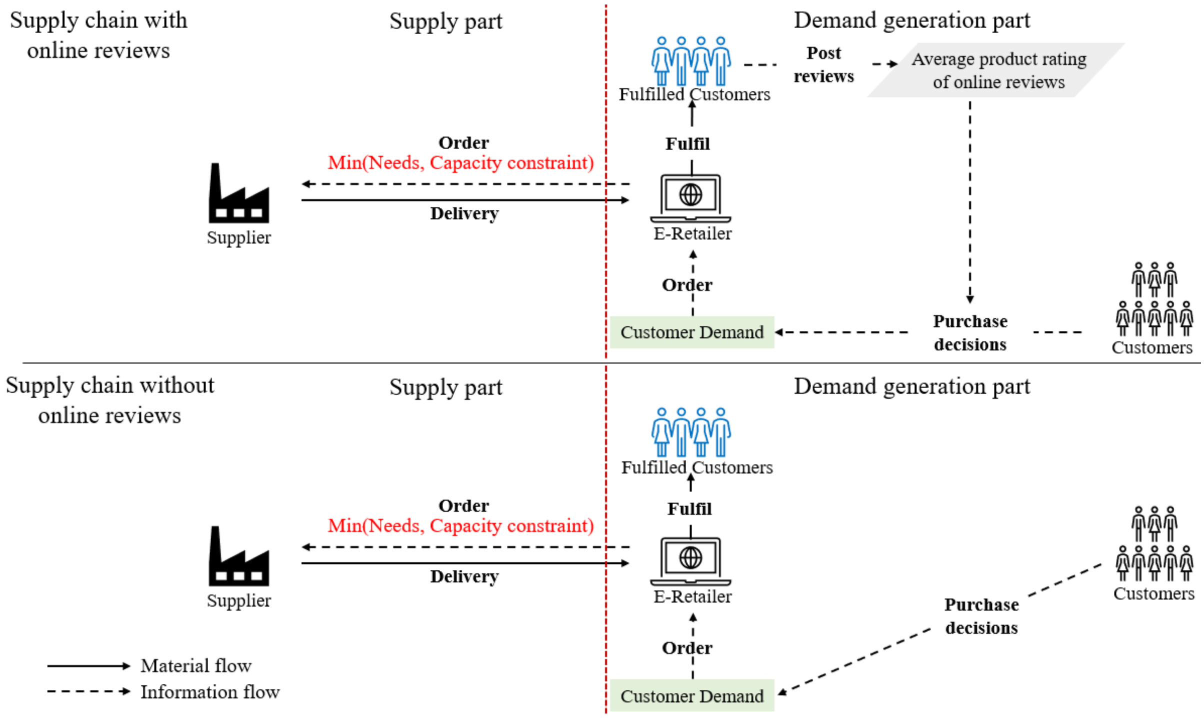

Figure 1. A capacitated supply chain model with/without online reviews

3.1 Model formulation

This paper starts from modelling demand generation, 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 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 it is only determined by customer preference. The utility derived from experience attribute, on the other hand, depends on the quality level of the product once delivered, with better quality leading higher utility.

The relationship between utility and the product attributes can be expressed as $u = q + x - p$, where u represents utility for customer, q represents quality (i.e. experience attribute), x represents preference (i.e. search attribute) and p represents price. Before purchasing, a customer i in period t has full knowledge on search attributes, and thus knows the utility derived from it (x_{it}) based on their preference, but can only estimate the value of the real product quality. For their estimation on quality, we assume every customer has the same value, notated q^e when there is no online review (Li and Hitt, 2008 & 2010; Hu et al., 2017). Therefore, customer estimated utility 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, we normalise the utility of the best substitute as 0 (Li and Hitt, 2008). Customers will decide to buy the products only if u_{it}^e is greater than 0.

When there are online reviews providing a rating, then q^e will be influenced by the average rating in period t (notated as $\bar{R}_t$) in the review system observed by the customer. The generation of $\bar{R}_t$ will be discussed later. Here, arguing from the perspective of bounded rationality, Li and Hitt (2008) assume that each customer's q^e will be updated equal to $\bar{R}_t$. We can thus put a unified equation for estimated utility u_{it}^e as

$$u_{it}^e = \begin{cases} q^e + x_{it} - p, & \text{no review} \\ \bar{R}_t + x_{it} - p, & \text{review available} \end{cases} \tag{1}$$

Therefore, when a customer i in period t has their $u_{it}^e > 0$, they will order the product, otherwise they simply leave. For the case of no review in equation (1), this also fits the first period when review system is used, as nobody would have posted on the review system in 'period 0'. There can also be 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 case, the equation for the 'no review' condition will always apply until reviews are posted by customers.

After purchasing and receiving the product, the real utility for customer i in period t after consuming the product is

$$u_{it} = q_{it} + x_{it} - p \tag{2}$$

where q_{it} is the real product quality. Based on Li and Hitt (2008), we here assume q_{it} follows a symmetric $Beta(1,1)$ distribution, which is mathematically equivalent to a uniform distribution i.e. $q_{it} \sim U(0,1)$. To check the robustness of our results with different distributions of q_{it}, we conducted an extensive sensitivity analysis with other distributions commonly seen in online review studies such as symmetric Beta distribution (Li and Hitt, 2008) and normal distribution (Hu et al., 2017; Ellison and Fudenberg, 1995; Papanastasiou and Savva, 2017). The analysis shown in Appendix 1 confirms that our results are robust to these different distributions. In addition, we assume q_{it} and x_{it} are not correlated with each other, as the purpose of this paper is not to investigate the online review properties alone but to work as exploratory research on the interaction between online reviews and capacitated supply chain.

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. Faced with unfamiliar products, customers can under-estimate their quality (Li and Hitt, 2008). By contrast, the products may also be excessively advertised (Shen et al., 2018), leading customers' over-estimation on quality. Therefore, it is more sensible to consider the adoption decisions under these two biased estimation scenarios and so we consider the situations of under-estimated quality and over-estimated quality. According to Li and Hitt (2008), we assume the q^e is 0.3 for under estimation scenario. Symmetrically, we choose q^e as 0.7 when quality is over-estimated. In other words, the over-estimation case means $q^e > E(q_{it})$ while under-estimation case $q^e < E(q_{it})$. The details for quality estimation exploration are discussed in Section 3.2.

Because of the supply chain capacity constraints and replenishment policy, stock-outs can occur and customers cannot be fulfilled until products are replenished. In this paper, we assume that customers who cannot be fulfilled when facing a stock-out condition will leave. In other words, we assume that no back-order is allowed and unfulfilled customers will become lost sales (Turrisi et al., 2013; Dominguez et al., 2018). Such an assumption can be justified. First, as E-retailing is almost a perfectly competitive market, if customers cannot be fulfilled immediately, they can directly turn to other substitutes without waiting. Second, if the supply chain capacity is lower than the mean market demand, if back-order is allowed, the back-order volume can be accumulated and customers' waiting time lengthened accumulatively as well. Even though customers may tolerate being in the waiting list at the beginning, the accumulated waiting time can result in later customers give up. For a deeper discussion on lost sales and waiting, we refer interested readers to Keith et al. (2017).

For those customers who are fulfilled and receive the products, they experience the products and obtain full knowledge on 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}. For those customers unwilling to post, no rating is recorded. Empirical research has identified many factors that influence the probability of a consumer posting a review including:

- personal factors such as age, gender and a desire to help others (Gonçalves et al., 2018);
- satisfaction with the product (Thakur, 2018), with extreme positive or negative experiences increasing this probability (Schoenmueller et al., 2020);
- trust and engagement with the seller (Thakur, 2018; Wu et al., 2018);
- sales volume, with a greater inclination to post for less popular products (Dellarocas et al., 2010);

- number of previous posts (Dellarocas et al., 2010).

However, when aggregated across all users, empirical studies suggest posting probabilities of between 8% and 11% (Nielsen, 2006; Bronner and De Hoog, 2010; Google, 2015). Therefore, we assume the probability of each customer posting reviews equal to 10% (Bhole and Hanna, 2018).

The e-commerce system will generate the rating for 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 bounded in 0 to 1 for any $t > 1$. Some online retailers such as Amazon do not share information about the algorithms in their online rating system, although the approach is based upon more than a simple average (Rubin, 2015). Others suggest that only reviews over a certain time frame are included – for example, Taobao only considers reviews over a 6-month period (Taobao Help Centre, 2021). However, there are also retailers which average all reviews – by examining the reviews for randomly sampled products, we identified this to be the case for major retailers such as Argos in the UK (http://www.argos.co.uk) and Sears in the USA (http://www.sears.com). Therefore, based on the empirical examples like Argos and Sears, we believe our modelling approach on rating calculation is consistent with practice.

Also, consistent with Jiang and Guo (2015), Hu et al. (2017), and Li and Hitt (2008), we assume 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(s) 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. $u_{it}^e = \bar{R}_t + x_{it} - p$).

Following the demand process, the supply side of the model can be formulated. We follow the well-developed model in Dejonckheere et al. (2003 & 2004), Potter and Lalwani (2008), Li and Disney (2014) and Dominguez et al. (2020). First, in every period, there are customers visiting the e-commerce site. Consistent with Jiang and Guo (2015) and Li and Hitt (2008), we assume 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

$$D_t = \sum_{i=1}^{N} f(u_{it}^e), where\ f(a) = \begin{cases} 0, a \leq 0 \\ 1, a > 0 \end{cases} \tag{3}$$

After observing the demand, the company will use available inventory for fulfilment. 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 is the lead time for replenishment system. Here we assume lead time is 4 periods. The fulfilled demand which is company's sales is notated as D_t^*, thus:

$$D_t^* = min\ (O_{t-L} + I_{t-1}, D_t) \tag{4}$$

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

$$I_t = max\ (I_{t-1} + O_{t-L} - D_t, 0) \tag{5}$$

$$WIP_t = WIP_{t-1} + O_{t-1} - O_{t-L} \tag{6}$$

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

$$F_t = \alpha * D_t + (1 - \alpha) * F_{t-1} \tag{7}$$

We assume 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). According to Syntetos et al. (2011), α is specified as 0.2.

Finally, based on forecasting, inventory level, and work-in-process level, the company will place an order with negative order quantity not allowed. However, as the supply chain is capacitated, the number of products that the company needs to order cannot exceed capacity constraint (i.e. $CapCon$):

$$O_t = min\big(max\big((L+1) * F_t - I_t - WIP_t, 0\big), CapCon\big) \quad (8)$$

This way of modelling the constraint is consistent with the LO approach discussed earlier (Costa et al., 2021; Cannella et al., 2018; Ponte et al., 2017).

Moreover, by selling products the company can obtain revenue but also generate supply chain related costs. We assume that the company will have a unit cost for producing each product, a holding cost and a lost sales penalty. Consistent with Ketzenberg et al. (2000), Hill (2007) and Metters (1997), we assume there is no ordering cost in our model. Our 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 minimum number of orders across all experiments.

To achieve an exhaustive research design, we set price as 1 per unit, which leads the positive sales but not cover the whole market for all scenarios. We adopt 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 production cost and cost of capital used for production. Metters (1997) specifies that the sales price is 40% higher than production costs, while the annual cost of capital is 13%. This latter figure gives a weekly cost of capital of 0.25% (i.e. $\frac{13\%}{52weeks}$) 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 our lead time is assumed as four periods, we calculate a three-period cost of capital for each product (there is an extra period for reviewing orders, see Dejonckheere et al., 2003). As we set the sales price as 1 per unit and, using the relationships expressed in Metters (1997), the combined production cost and cost of capital for production is reasonably assumed as 0.7 (i.e. $\frac{1}{1+40\%} * \left(1 + (1 - 0.9975^3)\right) \approx 0.7$). The combined production cost and cost of capital for production, 0.7, is thus the unit cost of the product.

Also, consistent with Metters (1997), the ratio of annual holding cost to unit cost 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 is usually around 20% or 30% of the unit cost (Tuovilia, 2020). Based on the unit cost 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, we also conducted sensitivity analysis (see Section 4) to the inventory cost, and the analysis shows our simulation results are robust to the inventory cost assumptions.

Finally, the lost sales penalty is considered as an independent variable for our following experiment design, and three levels are assumed, namely 0, 50% and 100% of the unit cost (Metters, 1997), so 0, 0.35 and 0.7 per unit respectively. 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 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 e-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, we thus follow Metters (1997) and include the lost sales penalty greater than 0 to make our model more realistic.

To sum up, the profit can be derived as follows:

$$Total\ Profit = Total\ Revenue - Total\ Holding\ Cost - Total\ Lost\ Sales\ Penalty \tag{9}$$

where each term is defined as:

$$Total\ Revenue = (Price - Unit\ Cost) * Total\ sold\ Units$$

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

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

3.2 Experimental design

We show the values of parameters, independent variables, and the performance measure in Table 3. In this paper, the main independent variable is adopting/not adopting online reviews in the capacitated supply chain. We also take other independent variables under consideration. The first variable is quality estimation as {over-estimation, under-estimation} which is equal to {0.7, 0.3}. Another independent variable is the capacity constraint ($CapCon$) with three levels, namely {Tight, Medium, Loose} which are quantified as {10, 25, 40} respectively. The Tight constraint is lower than mean demand in the under-estimation scenario while the Loose constraint is higher than the mean demand in the over-estimation scenario; the Medium constraint lies between these. Finally, the lost sales penalty has three levels, namely {Low, Moderate, High} which equal {0, 0.35, 0.7}. To measure performance, we calculate the profit of the supply chain.

Table 3. Experiment parameters and variables.

Experiment design	
Parameters	
q_{it}: real product quality	$U \sim (0,1)$
x_{it}: customer preference	$U \sim (0,1)$
p: product price	1
α: forecasting smoothing parameters	0.2
L: lead time	4
N: customers each period (including all types of customers)	50
Unit Cost per 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)}
Lost sales penalty per product	{0 (Low), 0.35 (Moderate), 0.7(High)}
Performance Measure	
Profit	

We adopt a full factorial experimental approach based on the independent variables, where 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. Based on the suggestions of Yang et al. (2011) and Cannella et al. (2018), the replications should be high enough to meet the criterion that the half-width 95% confidence interval is lower than 10% of the mean. As our simulation period is very long, such criterion can be easily met with five replications. The simulation results are then analysed by using Analysis of Variance (ANOVA). We conducted Shapiro-Wilk test and Levene's test to check the assumption of normality and homogeneity of variance, and no violation of the assumptions is found.

3.3 Simulation verification

The simulation is built in R programming language using RStudio. We conducted thorough validation and verification for our model. The logic of the mathematical model is validated from the developed models (e.g. Dejonckheere et al., 2003, Li and Hitt et al., 2008) and real-world situations based on group discussions amongst the research team. To verify the model implementation process, the model is divided into different submodules. For the supply chain modules, we adopted the same input as Dejonckheere et al. (2004) and compared our output value with theirs; no statistically significant difference exists. For demand side modules, one author compared simulation and analytical results, with no statistically significant difference existing between the two. In addition, this author also used Excel sheets and hand calculations when necessary to triangulate the simulation process accuracy. All verifications show that our model has good accuracy.

4. Result analysis

The ANOVA results in Table 4 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 explore the influence of online reviews in performance, analysis of main and interaction effects of online review adoption will be the focus, but skip the effects without it (i.e. the main and interaction effects only including other variables).

Table 4. ANOVA results

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: lost sales penalty level; CC: capacity constraint; QE: quality estimation.

For the main effect of online review adoption on supply chain performance, Table 5 reveals that, on average, adopting online reviews in a capacitated supply chain will lead higher profit than not adopting them. Specifically, online review adoption leads to a 33% profit increase compared with no review scenario.

Table 5. Main and first order interaction effects of online review adoption on supply chain profit.

		No online reviews	Adopt online reviews
Main effect		52668	70125
First Order Interaction		**No online reviews**	**Adopt online reviews**
Quality Estimation	Under-estimation	56609	70095
	Over-estimation	48728	70155
Lost Sales Penalty	Low	92484	100526
	Moderate	52693	70212
	High	12827	39637
Capacity Constraint	Loose	125117	125521
	Medium	71167	123156
	Tight	-38279	-38302

Table 5 also presents the three first order interaction effects between online review adoption and quality estimation, lost sales penalty, and capacity constraint. For quality estimation, online review adoption leads to higher profits in the supply chain, although the profit difference when quality is under-estimated is slightly smaller than the difference in quality over-estimation scenario. For lost sales penalty, higher profit can always be observed when adopting online reviews as well. The profit difference is larger when the lost sales penalty level is high, while it is less apparent when penalty level is moderate and low. Finally, for capacity constraint level, the graph presents some evidence on the diverse influence of online review adoption. When the capacity constraint level is medium, significant profit increase can be obtained by adopting reviews compared with no review case. However, when capacity constraints are loose or tight, the influence of online reviews on profit nearly diminishes and almost no difference on profit is obtained from adopting them. This suggests complexity in the influence of online reviews on profit. In other words, although first impressions of the main and first order effect seem to imply that online review adoption enables the supply chain more profitable, in certain scenarios such influence is dubious. Therefore, to better reveal the mechanism of online review influence, it is necessary to examine the second and third order interactions to capture the full picture.

Table 6 presents the second order effects, and the interaction effects between online review adoption, quality estimation and both lost sales penalty and capacity constraints. The second order interaction effect containing lost sales penalty 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 (i.e. influenced by over-stated advertisements), more profit can be gained by adopting online reviews only when the lost sales penalty level is moderate or high. However, if quality under-estimation occurs, more profit can be obtained through using online reviews when the penalty level is low or moderate.

Table 6. Second order interaction effects on supply chain profit

		No online reviews	**Adopt online reviews**
Quality Estimation	**Lost Sales Penalty**		
Under-estimation	Low	66850	100558
	Moderate	56659	70117
	High	46316	39610
Over-estimation	Low	118118	100493
	Moderate	48727	70307
	High	-20662	39663
Quality Estimation	**Capacity Constraint**		
Under-estimation	Loose	74285	125531
	Medium	74314	123180
	Tight	21227	-38425
Over-estimation	Loose	175949	125511
	Medium	68019	123131
	Tight	-97785	-38178

For the second order interaction involving capacity constraints, different influences of online reviews can also be observed. If quality is over-estimated, online review adoption leads 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 reduce profit once the level is tight.

Analysis of the second order interaction reveals the diversity of online review influence on supply chain profit, and that review adoption does 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, such as different lost sales penalties in the market and capacity constraints.

Finally, the third order interaction is analysed to further investigate such diverse influence. To better analyse and visualise the third order interaction effect, the profit between adopting online reviews and not adopting them is summarised by different scenarios in Table 7. 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.

Table 7. Third order interaction effects on supply chain profit

Quality Estimation	**Lost Sales Penalty**	**Capacity Constraint**	**No online reviews**	**Adopt online reviews**
Under-estimation	Low	Loose	74716	125609
		Medium	74840	125067
		Tight	50994	51000
	Moderate	Loose	74351	125509
		Medium	74339	123104
		Tight	21287	-38262
	High	Loose	73786	125474
		Medium	73762	121370
		Tight	-8600	-128013
Over-estimation	Low	Loose	175854	125460
		Medium	127500	125020
		Tight	51000	51000
	Moderate	Loose	175996	125518
		Medium	67983	123149
		Tight	-97799	-37746
	High	Loose	175996	125555
		Medium	8575	121224
		Tight	-246557	-127788

If quality is over-estimated, adopting online reviews will always lead to less profit when capacity constraint level is loose. When the constraint level is medium, adopting online reviews makes little difference when the lost sales penalty level is low, but with a moderate or high lost sales penalty, more profit can be obtained if online reviews are adopted. With tight capacity constraints, online reviews are again beneficial in moderate or high lost sales penalty scenarios, albeit in reducing losses rather than increasing profit. On the other hand, when quality is under-estimated, if the constraint level is loose or medium then adopting online reviews can lead to more profit for all penalty scenarios. For the case of tight capacity constraint levels 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 review is adopted, with 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 Table 8, the *value differences* related to revenue, holding cost, lost sales penalty, and profit are presented, where the difference here is equal to the value when online reviews are adopted minus the value without online reviews. For example, the 'Total revenue difference' in Table 8 represents the revenue when online reviews are adopted minus the revenue without online reviews.

Table 8. Value difference of revenue, costs, and profit

	Over-estimation			Under-estimation		
Lost sales penalty	Low penalty			Low penalty		
Capacity constraint	Loose constraint	Medium constraint	Tight constraint	Loose constraint	Medium constraint	Tight constraint
Total Profit difference	-50394	-2480	0	50893	50227	6
Total Revenue difference	-51062	-1784	0	51629	49760	0
Total Holding Cost difference	-667	696	0	737	-466	-6
Total Lost sales Penalty difference	0	0	0	0	0	0
Lost sales penalty	Moderate penalty			Moderate penalty		
Capacity constraint	Loose constraint	Medium constraint	Tight constraint	Loose constraint	Medium constraint	Tight constraint
Total Profit difference	-50478	55166	60053	51158	48765	-59549
Total Revenue difference	-51097	-1807	0	51387	49614	0
Total Holding Cost difference	-665	701	0	734	-463	-6
Total Lost sales Penalty difference	46	-57674	-60052	-504	1313	59556
Lost sales penalty	High penalty			High penalty		
Capacity constraint	Loose constraint	Medium constraint	Tight constraint	Loose constraint	Medium constraint	Tight constraint
Total Profit difference	-50441	112649	118769	51688	47608	-119413
Total Revenue difference	-51016	-1794	0	51408	49641	0
Total Holding Cost difference	-666	699	0	733	-452	-6
Total Lost sales Penalty difference	91	-115142	-118769	-1014	2485	119419

Table 8 shows that holding cost differences are very small and therefore contribute little to the influence of online review adoption decisions. To verify this, we conducted a sensitivity analysis on the unit holding cost. However, even the value of unit holding cost is amplified by 10 times, the influence of total holding cost different on the profit difference is still very small. Thus, it is not necessary to consider holding cost when deciding on the use of online reviews. In addition, the difference in revenue and lost sales penalty presents roughly opposite effects on the profit difference, and these effects are essentially generated from the interaction between online review adoption decisions and other independent variables.

To explain the relationship in detail, when quality is over-estimated, customers are falsely over-optimistic on product quality, and market demand will increase. Once online reviews are adopted, customer expectations on quality are corrected and market demand will decrease to be lower than the case 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 will prefer not to adopt online reviews as they can have more market demand and generate more profit by fulfilling this. However, if the capacity constraint gets tighter, only limited products can be ordered to fulfil customers. In this case, if companies still not adopt online reviews, there will be higher market demand and some of them cannot be fulfilled. These unfulfilled customers incur a lost sales penalty. Therefore, companies now will prefer to adopt online reviews to decrease the penalty level. These insights explain why adopting reviews leads to profit loss when the capacity constraint level is loose and lost sales penalty is low, but results in significant profit increases when the capacity constraint level is tighter and lost sales penalty is higher.

When quality is under-estimated, adopting online reviews corrects customer quality estimation bias and can increase more market demand. In this case, if capacity constraint is loose enough, companies will prefer to adopt online reviews as more customer demand can be fulfilled without losing 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 lost sales penalty higher, online review adoption leads to more market demand, but the company cannot fulfill all of this and so lost sales penalties increase. The company now will prefer not to adopt online review, which essentially explains why the profit will be lower if reviews are adopted the when constraint level is tighter and penalty level is higher.

5. Discussion: explaining the mechanism

Based on the results analysed in section 4, Figure 2 visualises the mechanism that connects each independent variable and their influence on supply chain profit. The relative change in different scenarios between revenue and lost sales penalty determines whether the company can benefit from adopting online reviews. What should be noticed here is that inventory holding cost changes caused by online reviews are not considered, as the above analysis illustrated such change has little impact on the profit.

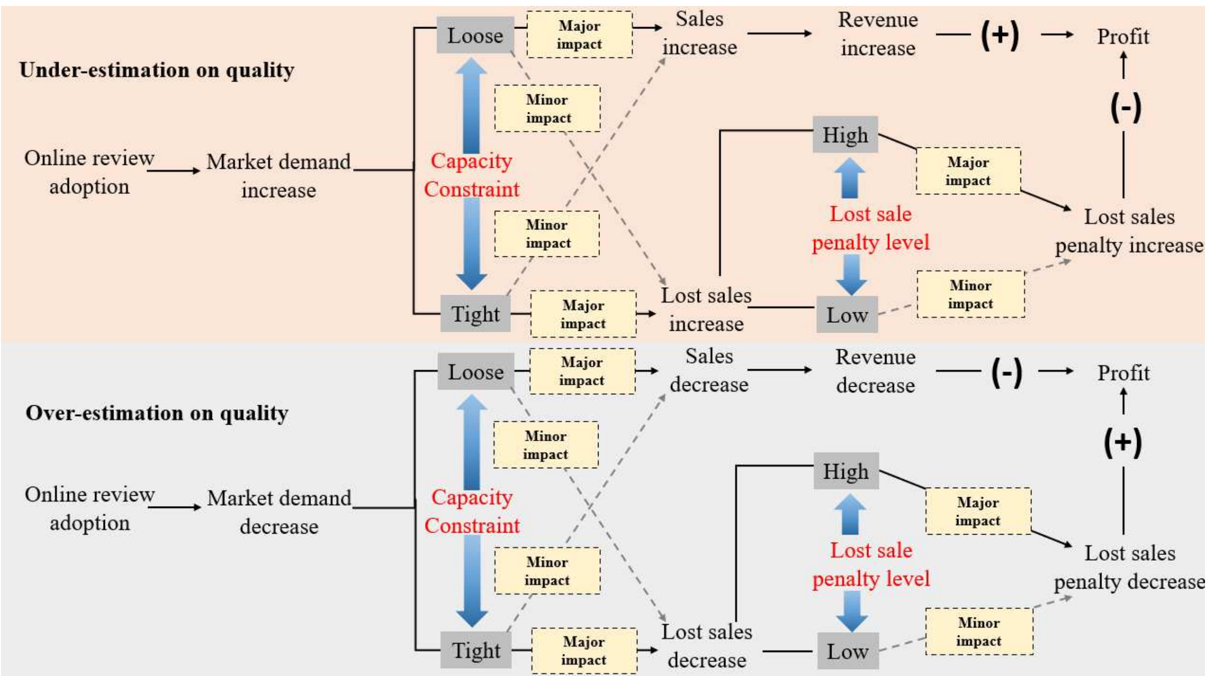

Figure 2. Mechanism of online review influence on capacitated supply chain

Specifically, when quality is under-estimated by customers, adopting online reviews can correct this under-estimation bias and increase the market demand. If capacity constraint is loose, the increased demand can be fulfilled, which increases the revenue and eventually the profit. However, if the capacity constraint is very tight, the increased demand cannot be fully fulfilled, leading to more lost sales. Under such a case, if the lost sales penalty level is very low, the increased lost sales will not lead to a high increase in lost sales penalty. Once penalty level is high, the increased lost sales penalty will then cause a severe profit loss. Therefore, the decision to adopt online reviews is effectively determined by the ability of the supply chain to fulfil this increased demand, and the penalty costs from failing to do so.

When quality is over-estimated, adopting online reviews can correct customer over-estimation bias and lead the market demand to decrease. When the capacity constraint is tight, the lost sales of the company can thus be decreased, as the demand generated from over-estimation bias is higher than what can be fulfilled. If the lost sales penalty level is very high, the reduction of lost sales will thus decrease the total lost sales penalty, while it generates small impact if penalty level is low. On the contrary, if the capacity constraint is loose, the fulfilment level is high even in the over-estimation scenario. Thus, under such circumstances, adopting online reviews does not affect the lost sales but decreases sales, which eventually leads to a profit reduction. Therefore, if customers over-estimate product quality, then there is less incentive to use online reviews. The exception to this is when capacity is tight because the reviews align demand and supply more effectively and reduce lost sales penalties.

The proposed mechanism also leads 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 estimate 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.

The above results show that the influence of online review adoption highly depends on quality estimation, capacity constraint level, 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 performance, organisational characteristics should be a good fit with 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 paper thus raises awareness that adopting or not adopting online reviews should also fit a company's specific contingencies (i.e. quality estimation, capacity constraint level, and 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 considered in terms of the whole supply chain system profitability.

6. Conclusion and implications

In this paper, the influence of online reviews on supply chain profitability is explored, analysing when companies should adopt or not adopt online reviews in their supply chain operations. Through extending a capacitated supply chain model to incorporate online reviews, the impact on supply chain profitability is explored using simulation experiments. The results reveal that overall, online reviews can enhance profitability in the supply chain, but there is complexity and such effect depends upon other factors including customer quality estimation, capacity constraints, and lost sales penalties. Therefore, companies' adoption decisions on online reviews should fit different contextual factors. An interesting but counterintuitive phenomenon is discovered, where companies can benefit from decreasing customer quality estimation or keeping customers under-estimate product quality by adopting/not adopting online reviews. Such findings inform managers on the diverse influences of online reviews on supply chain profitability.

6.1 Academic and managerial implications

This paper has both research and practical implications. Considering the research implications, first, there is a dearth of research linking online reviews to supply chain management, and none of the existing studies consider online reviews from a capacitated supply chain perspective. Therefore, the findings enhance the understanding of the influence of online reviews on capacitated supply chain. Compared with previous studies of online reviews in supply chain management, this paper evaluates the influence of online reviews from the whole supply chain system rather than just from market demand aspect, which presents a holistic view to better measure the value of online reviews.

Second, this paper models customer heterogeneity in the process of purchase and review posting and derives the supply chain demand from considering each individual customer's behaviour. As Section 2.2 shows that the majority of the capacitated supply chain papers assume a general random distribution of customer demand without considering the heterogeneous behaviours of the customers. Thus, this paper's novel approach contributes to the better modelling of the customers' online shopping behaviours and the development of a more realistic model. More generally, there are few papers relevant to this study that adopt a simulation approach, further highlighting the methodological contribution. As reflected in Section 3, the presence of capacity constraints make the model nonlinear and therefore hard to be analytically tractable. Simulation works as a powerful tool to overcome the nonlinearity and intractability, providing the methodological basis for future research to investigate this topic.

Third, the discovery of counter-intuitive outcomes highlights the complex influence of online reviews on the capacitated supply chain performance. Although this paper does not specifically aim for optimising the supply chain performance, the insights obtained from this paper may pave the way for future studies on optimising the performance of the capacitated supply chain in an e-commerce context, from an online review adoption perspective.

Turning to practical implications, the results inform companies and managers to make better decisions on adopting online reviews. For those working in capacitated environments, the overall findings suggest that online reviews can bring the biggest supply chain profit benefits when capacity is neither loose nor tight, by ensuring customer demand remains within limits. However, if customers are consistently incorrectly estimating quality, then the use of reviews can have significant impact. 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.

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.

6.2 Limitations and future directions

As an exploratory paper, there are several limitations to our model that should be acknowledged and can be explored in the future research. First, we assume the online reviews are all real, and each review will truly reflect customers real quality level. However, in real world, companies may post promotional reviews (Mayzlin, 2006; Dellarocas, 2006) to generate higher customer demand. It can be equally possible that companies benefit from posting bad reviews as suggested from our results. Therefore, future research can extend our model to explore such manipulations, which may provide valuable insights for developing mechanisms to prevent review fraud.

Second, we assume the product is not returnable, although there is evidence that e-commerce can be a significant generator of product returns, especially for products like clothing (Statista, 2020). Therefore, it can be promising to study the influence of online reviews in supply chain models incorporating product return, reverse logistics, as well as recycling and remanufacturing.

Finally, this paper only considers supply chain profitability as the performance measure. However, previous studies in Section 2 suggest that capacity constraints are also an important influencer of supply chain operational performance such as bullwhip effect. Therefore, future studies can investigate the influence of online reviews on bullwhip effect. Due to the customer heterogeneity induced by online reviews, future studies can apply hybrid simulation, such as combining agent-based modelling and discrete-event simulation or combining agent-based modelling and system dynamics to research this topic. This is because discrete-event simulation and system dynamics are usually applied for bullwhip studies (e.g. Dejonckheere et al., 2003; Dominguez et al. 2019; Chatfield and Pritchard, 2013) while agent-based modelling adopts a 'bottom-up' manner to capture agent behaviours (Wilensky and Rand, 2015), which can effectively reflect the customer heterogeneity induced by online reviews. Through hybrid simulation, it is expected that more complicated customer behaviours and supply chain structures can be studied from an online review perspective.

Acknowledgements

We sincerely thank the associate editor and two anonymous referees for their helpful feedback and comments.

Reference

Angelus, A. and Zhu, W., 2017. Looking upstream: Optimal policies for a class of capacitated multi‐stage inventory systems. *Production and Operations Management*, *26*(11), pp.2071-2088.

Babić Rosario, A., Sotgiu, F., De Valck, K. and Bijmolt, T.H., 2016. The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), pp.297-318.

Bhole, B. and Hanna, B., 2017. The effectiveness of online reviews in the presence of self-selection bias. *Simulation Modelling Practice and Theory*, *77*, pp.108-123.

Boute, R.N., Disney, S.M., Lambrecht, M.R. and Van Houdt, B., 2009. Designing replenishment rules in a two-echelon supply chain with a flexible or an inflexible capacity strategy. *International Journal of Production Economics*, 119(1), pp.187-198.

Bronner, F., and De Hoog, R., 2010. Consumer generated versus marketer generated websites in consumer decision making. *International Journal of Market Research, 52*(2), pp.231–248.

Cai, X., Li, J., Dai, B. and Zhou, T., 2018. Pricing strategies in a supply chain with multi-manufacturer and a common retailer under online reviews. *Journal of Systems Science and Systems Engineering*, *27*(4), pp.435-457.

Cannella, S., Ciancimino, E. and Marquez, A.C., 2008. Capacity constrained supply chains: a simulation study. *International Journal of Simulation and Process Modelling*, *4*(2), pp.139-147.

Cannella, S., Dominguez, R. and Framinan, J.M., 2017. Inventory record inaccuracy–The impact of structural complexity and lead time variability. *Omega*, *68*, pp.123-138.

Cannella, S., Dominguez, R., Ponte, B., & Framinan, J. M., 2018. Capacity restrictions and supply chain performance: Modelling and analysing load-dependent lead times. *International Journal of Production Economics*, *204*, 264-277.

Chan, H.K., Lacka, E., Yee, R.W. and Lim, M.K., 2017. The role of social media data in operations and production management. *International Journal of Production Research*, *55*(17), pp.5027-5036.

Chatfield, D.C. and Pritchard, A.M., 2013. Returns and the bullwhip effect. *Transportation Research Part E: Logistics and Transportation Review*, *49*(1), pp.159-175.

Chong, A.Y.L., Ch'ng, E., Liu, M.J. and Li, B., 2017. Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews. *International Journal of Production Research*, *55*(17), pp.5142-5156.

Competition and Markets Authority, 2016. Online reviews and endorsements: advice for businesses. https://www.gov.uk/government/publications/online-reviews-and-endorsements-advice-for-businesses [Accessed: 7 May 2021].

Costa, A., Cannella, S., Corsini, R.R., Framinan, J.M. and Fichera, S., 2020. Exploring a two-product unreliable manufacturing system as a capacity constraint for a two-echelon supply chain dynamic problem. *International Journal of Production Research*, pp.1-29.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R. and Towill, D. R., 2004. The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective. *European Journal of Operational Research*, *153*(3), 727-750.

Dejonckheere, J., Disney, S.M., Lambrecht, M.R. and Towill, D.R., 2003. Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research*, *147*(3), pp.567-590.

Dellarocas, C., 2006. Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management science*, *52*(10), pp.1577-1593.

Dellarocas, C., Gao, G. and Narayan, N., 2010. Are consumers more likely to contribute online reviews for hit or niche products? *Journal of Management Information Systems, 27*(2), pp.127-158.

Dominguez, R., Cannella, S., Barbosa-Póvoa, A.P. and Framinan, J.M., 2018. Information sharing in supply chains with heterogeneous retailers. *Omega*, *79*, pp.116-132.

Dominguez, R., Cannella, S., Ponte, B. and Framinan, J.M., 2020. On the dynamics of closed-loop supply chains under remanufacturing lead time variability. *Omega*, *97*, p.102106.

Dominguez, R., Ponte, B., Cannella, S. and Framinan, J.M., 2019. On the dynamics of closed-loop supply chains with capacity constraints. *Computers & Industrial Engineering*, *128*, pp.91-103.

Donaldson, L., 2001. *The Contingency Theory of Organizations*. Sage.

Ellison, G. and Fudenberg, D., 1995. Word-of-mouth communication and social learning. *The Quarterly Journal of Economics*, *110*(1), pp.93-125.

Fan, Z.P., Che, Y.J. and Chen, Z.Y., 2017. Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis. *Journal of Business Research*, *74*, pp.90-100.

Freeman, N., Mittenthal, J., Keskin, B. and Melouk, S., 2018. Sourcing strategies for a capacitated firm subject to supply and demand uncertainty. *Omega*, *77*, pp.127-142.

Georgiadis, P., Vlachos, D. and Tagaras, G., 2006. The impact of product lifecycle on capacity planning of closed‐loop supply chains with remanufacturing. *Production and Operations management*, 15(4), pp.514-527.

Glock, C.H. and Ries, J.M., 2013. Reducing lead time risk through multiple sourcing: the case of stochastic demand and variable lead time. *International Journal of Production Research*, 51(1), pp.43-56.

Glock, C.H., 2012. Lead time reduction strategies in a single-vendor–single-buyer integrated inventory model with lot size-dependent lead times and stochastic demand. *International Journal of Production Economics*, 136(1), pp.37-44.

Gonçalves, H.M., Silva, G.M. and Martins, T.G., 2018. Motivations for posting online reviews in the hotel industry. *Psychology and Marketing, 35*(11), pp.807-817.

Google, 2015. After making your purchase did you do any of the following online?. *Statista*. https://www.statista.com/statistics/376459/post-purchase-online-activities-united-kingdom/ [Accessed: 7 May 2021].

Gu, B. and Ye, Q., 2014. First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management*, *23*(4), pp.570-582.

Guo, M., Liao, X., Liu, J. and Zhang, Q., 2020. Consumer preference analysis: A data-driven multiple criteria approach integrating online information. *Omega*, *96*, p.102074.

Gupta, V., Ivanov, D. and Choi, T.M., 2021. Competitive pricing of substitute products under supply disruption. *Omega*, *101*, p.102279.

Hill, R. M., 2007. Continuous-review, lost-sales inventory models with Poisson demand, a fixed lead time and no fixed order cost. *European Journal of Operational Research*, *176*(2), pp. 956-963.

Hou, R., de Koster, R. and Yu, Y., 2018. Service investment for online retailers with social media—Does it pay off?. *Transportation Research Part E: Logistics and Transportation Review*, *118*, pp.606-628.

Hu, N., Koh, N. S. and Reddy, S. K., 2014. Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems*, *57*, 42-53.

Hu, N., Liu, L. and Zhang, J. J., 2008. Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. *Information Technology and Management*, *9*(3), 201-214.

Hu, N., Pavlou, P.A. and Zhang, J.J., 2017. On Self-Selection Biases in Online Product Reviews. *MIS Quarterly*, *41*(2), pp.449-471.

James, T.L., Calderon, E.D.V. and Cook, D.F., 2017. Exploring patient perceptions of healthcare service quality through analysis of unstructured feedback. *Expert Systems with Applications*, *71*, pp.479-492.

Jia, S.S., 2020. Motivation and satisfaction of Chinese and US tourists in restaurants: A cross-cultural text mining of online reviews. *Tourism Management*, *78*, p.104071.

Jiang, Y. and Guo, H., 2015. Design of consumer review systems and product pricing. *Information Systems Research*, *26*(4), 714-730.

Jin, J., Liu, Y., Ji, P. and Liu, H., 2016. Understanding big consumer opinion data for market-driven product design. *International Journal of Production Research*, *54*(10), pp.3019-3041.

Keith, D. R., Sterman, J. D., & Struben, J., 2017. Supply constraints and waitlists in new product diffusion. *System Dynamics Review*, *33*(3-4), 254-279.

Ketzenberg, M., Metters, R. and Vargas, V., 2000. Inventory policy for dense retail outlets. *Journal of Operations Management*, *18*(3), pp.303-316.

Khazanchi, D., 2005. Information technology (IT) appropriateness: The contingency theory of "FIT" and IT Implementation in small and medium enterprises. *Journal of Computer Information Systems*, *45*(3), pp.88-95.

Ko, D.G., Mai, F., Shan, Z. and Zhang, D., 2019. Operational efficiency and patient-centered health care: A view from online physician reviews. *Journal of Operations Management*, *65*(4), pp.353-379.

Korfiatis, N., Stamolampros, P., Kourouthanassis, P. and Sagiadinos, V., 2019. Measuring service quality from unstructured data: A topic modeling application on airline passengers' online reviews. *Expert Systems with Applications*, *116*, pp.472-486.

Kwark, Y., Chen, J. and Raghunathan, S., 2014. Online product reviews: Implications for retailers and competing manufacturers. *Information Systems Research*, *25*(1), pp.93-110.

Lau, R.S.M., Xie, J. and Zhao, X., 2008. Effects of inventory policy on supply chain performance: A simulation study of critical decision parameters. *Computers & Industrial Engineering*, *55*(3), pp.620-633.

Lau, R.Y.K., Zhang, W. and Xu, W., 2018. Parallel aspect-oriented sentiment analysis for sales forecasting with big data. *Production and Operations Management*, *27*(10), pp.1775-1794.

Li, J., Yu, Y. and Liu, C., 2019a. Product design crowdsourcing in a dual-channel supply chain: joint reviews from manufacturer and consumers. *International Transactions in Operational Research*.

Li, Q., Disney, S. M., and Gaalman, G. 2014. Avoiding the bullwhip effect using Damped Trend forecasting and the Order-Up-To replenishment policy. *International Journal of Production Economics*, *149*, pp. 3-16.

Li, X. and Hitt, L.M., 2008. Self-selection and information role of online product reviews. *Information Systems Research*, *19*(4), pp.456-474.

Li, X. and Hitt, L.M., 2010. Price effects in online product reviews: An analytical model and empirical analysis. *MIS Quarterly*, pp.809-831.

Li, Y., Li, G., Tayi, G.K. and Cheng, T.C.E., 2019b. Omni-channel retailing: Do offline retailers benefit from online reviews?. *International Journal of Production Economics*, *218*, pp.43-61.

Lin, W.J., Jiang, Z.B. and Wang, L., 2014. Modelling and analysis of the bullwhip effect with customers' baulking behaviours and production capacity constraint. *International Journal of Production Research*, *52*(16), pp.4835-4852.

Liu, Y., Jin, J., Ji, P., Harding, J.A. and Fung, R.Y., 2013. Identifying helpful online reviews: a product designer's perspective. *Computer-Aided Design*, *45*(2), pp.180-194.

Liu, Z., Gao, R., Zhou, C. and Ma, N., 2019. Two-period pricing and strategy choice for a supply chain with dual uncertain information under different profit risk levels. *Computers & Industrial Engineering*, *136*, pp.173-186.

Lodree Jr, E.J., 2007. Advanced supply chain planning with mixtures of backorders, lost sales, and lost contract. *European Journal of Operational Research*, *181*(1), pp.168-183.

Lui, T.W., Bartosiak, M., Piccoli, G. and Sadhya, V., 2018. Online review response strategy and its effects on competitive performance. *Tourism Management*, *67*, pp.180-190.

Mayzlin, D., 2006. Promotional chat on the Internet. *Marketing Science*, *25*(2), pp.155-163.

Metters, R., 1997. Quantifying the bullwhip effect in supply chains. *Journal of Operations Management*, *15*(2), 89-100.

Minnema, A., Bijmolt, T.H., Gensler, S. and Wiesel, T., 2016. To keep or not to keep: Effects of online customer reviews on product returns. *Journal of Retailing*, *92*(3), pp.253-267.

Morton, N.A. and Hu, Q., 2008. Implications of the fit between organizational structure and ERP: A structural contingency theory perspective. *International Journal of Information Management*, *28*(5), pp.391-402.

Nahmias, S. and Cheng, Y., 2009. *Production and Operations Analysis* (Vol. 6). New York: McGraw-Hill.

Nielsen, J., 2006. The 90-9-1 Rule for Participation Inequality in Social Media and Online Communities. https://www.nngroup.com/articles/participation-inequality/ [Accessed: 7 May 2021].

Öğüt, H., & Onur Taş, B. K., 2012. The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197-214.

Papanastasiou, Y. and Savva, N., 2017. Dynamic pricing in the presence of social learning and strategic consumers. *Management Science*, 63(4), pp.919-939.

Ponte, B., Wang, X., de la Fuente, D. and Disney, S.M., 2017. Exploring nonlinear supply chains: the dynamics of capacity constraints. *International Journal of Production Research*, *55*(14), pp.4053-4067.

Potter, A., and Lalwani, C., 2008. Investigating the impact of demand amplification on freight transport. *Transportation Research Part E: Logistics and Transportation Review*, *44*(5), 835-846.

Qi, A., Ahn, H.S. and Sinha, A., 2015. Investing in a shared supplier in a competitive market: Stochastic capacity case. *Production and Operations Management*, *24*(10), pp.1537-1551.

Qi, J., Zhang, Z., Jeon, S. and Zhou, Y., 2016. Mining customer requirements from online reviews: A product improvement perspective. *Information & Management*, *53*(8), pp.951-963.

Rubin, B.F., 2015. Amazon looks to improve customer-reviews system with machine. https://www.cnet.com/news/amazon-updates-customer-reviews-with-new-machine-learning-platform/ [Accessed: 7 May 2021].

Sahoo, N., Dellarocas, C. and Srinivasan, S., 2018. The impact of online product reviews on product returns. *Information Systems Research*, *29*(3), pp.723-738.

Schneider, M.J. and Gupta, S., 2016. Forecasting sales of new and existing products using consumer reviews: A random projections approach. *International Journal of Forecasting*, *32*(2), pp.243-256.

Schoenmueller, V., Netzer, O. and Stahl, F., 2020. The Polarity of Online Reviews: Prevalence, Drivers and Implications. *Journal of Marketing Research, 57*(5), pp.853-877.

See-To, E.W. and Ngai, E.W., 2018. Customer reviews for demand distribution and sales nowcasting: a big data approach. *Annals of Operations Research*, *270*(1-2), pp.415-431.

Sezgen, E., Mason, K.J. and Mayer, R., 2019. Voice of airline passenger: A text mining approach to understand customer satisfaction. *Journal of Air Transport Management*, *77*, pp.65-74.

Shapiro, C., 1983. Optimal pricing of experience goods. *The Bell Journal of Economics*, pp.497-507.

Shen, Bin, Yanhui Deng, Xin Wang, and Qingying Li., 2018. Overstated product sustainability: real cases and a game-theoretical analysis. *Annals of Operations Research,* pp.1-19.

Shen, W., Duenyas, I. and Kapuscinski, R., 2011. New product diffusion decisions under supply constraints. *Management Science*, *57*(10), pp.1802-1810.

Statista., 2020. Which of these kinds of articles have you sent back after an online order in the past 12 months? *https://www.statista.com/forecasts/997848/returns-of-online-purchases-by-category-in-the-uk* [Accessed 02 October 2020].

Sterman, J.D., 1989. Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science*, *35*(3), pp.321-339.

Su, Y. and Teng, W., 2018. Contemplating museums' service failure: Extracting the service quality dimensions of museums from negative on-line reviews. *Tourism Management*, *69*, pp.214-222.

Syntetos, A.A., Georgantzas, N.C., Boylan, J.E. and Dangerfield, B., 2018. Judgement and supply chain dynamics. In *System Dynamics* (pp. 219-260). Palgrave Macmillan, London.

Taobao Help Centre., 2021. How are the ratings of retailers calculated? https://helpcenter.taobao.com/servicehall/knowledge_detail?knowledgeId=1119285 *in Chinese*. [Accessed: 11 May 2021].

Teo, T.S. and King, W.R., 1997. Integration between business planning and information systems planning: an evolutionary-contingency perspective. *Journal of Management Information Systems*, *14*(1), pp.185-214.

Thakur, R., 2018. Customer engagement and online reviews. *Journal of Retailing and Consumer Services, 41*, pp.48-59

Tuovila, A., 2020. Inventory carrying cost. *Investopedia*. https://www.investopedia.com/terms/c/carryingcostofinventory.asp#:~:text=Inventory%20car rying%20cost%20is%20the,of%20its%20total%20inventory%20costs. [Accessed: 10 May 2021].

Turrisi, M., Bruccoleri, M. and Cannella, S., 2013. Impact of reverse logistics on supply chain performance. *International Journal of Physical Distribution & Logistics Management*.

Van Nguyen, T., Zhou, L., Chong, A.Y.L., Li, B. and Pu, X., 2020. Predicting customer demand for remanufactured products: A data-mining approach. *European Journal of Operational Research*, *281*(3), pp.543-558.

Vlachos, D., Georgiadis, P. and Iakovou, E., 2007. A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains. *Computers & Operations Research*, *34*(2), pp.367-394.

Walsh, G. and Möhring, M., 2017. Effectiveness of product return-prevention instruments: Empirical evidence. *Electronic Markets*, *27*(4), pp.341-350.

Wang, J., Zhou, Z. and Yu, M., 2019. Pricing models in a sustainable supply chain with capacity constraint. *Journal of Cleaner Production*, 222, pp.57-76.

Wilensky, U. and Rand, W., 2015. *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Mit Press.

Wu, J., Fan, S. and Zhao, J.L., 2018. Community engagement and online word of mouth: An empirical investigation. *Information and Management, 55*(2), pp.258-270.

Wu, J., Jiang, F. and He, Y., 2018. Pricing and horizontal information sharing in a supply chain with capacity constraint. *Operations Research Letters*, 46(4), pp.402-408.

Xiao, W. and Xu, Y., 2018. Should an online retailer penalize its independent sellers for stockout?. *Production and Operations Management*, 27(6), pp.1124-1132.

Yang, B., Liu, Y., Liang, Y. and Tang, M., 2019. Exploiting user experience from online customer reviews for product design. *International Journal of Information Management*, *46*, pp.173-186.

Yang, T., Wen, Y.F. and Wang, F.F., 2011. Evaluation of robustness of supply chain information-sharing strategies using a hybrid Taguchi and multiple criteria decision-making method. *International Journal of Production Economics*, *134*(2), pp.458-466.

Yang, W., Zhang, J. and Yan, H., 2021. Impacts of online consumer reviews on a dual-channel supply chain. *Omega*, 101, p.102266.

Zhang, H., Rao, H. and Feng, J., 2018. Product innovation based on online review data mining: a case study of Huawei phones. *Electronic Commerce Research*, *18*(1), pp.3-22.

Zhang, L., Chu, X. and Xue, D., 2019. Identification of the to-be-improved product features based on online reviews for product redesign. *International Journal of Production Research*, *57*(8), pp.2464-2479.

Zhao, X., Xie, J. and Leung, J., 2002. The impact of forecasting model selection on the value of information sharing in a supply chain. *European Journal of Operational Research*, *142*(2), pp.321-344.

Appendix 1

Sensitivity analysis of the real quality (q_{it}) distribution

In our model, we assume the distribution of real quality q_{it} follows uniform distribution $U(0,1)$. Other commonly used distributions for q_{it} include symmetric Beta distribution (Li and Hitt, 2008) and normal distribution (Hu et al., 2017; Ellison and Fudenberg, 1995; Papanastasiou and Savva, 2017). Therefore, to check the robustness of our results, we simulated different distributions for q_{it}. For comparability to the $U(0,1)$, we choose $Beta(2,2)$, $Beta(3,3)$, $N(0.5, 0.05^2)$, and $N(0.5, 0.2^2)$ to keep the same mean value (i.e. 0.5) but different variances.

In Table A1, the online review **Adoption decision** in each of the experimental scenarios are presented as 'Adopt', 'Not Adopt', and 'Indifference', which represents when the profit from adopting online reviews is statistically significantly higher, lower, or indifferent than not having online reviews, based on a 95% confidence interval. To check if our results are robust to different distributions of q_{it}, it is necessary to compare if the **Adoption decisions** in each scenario are the same across five distributions. Table A1 shows the **Adoption decisions** in each scenario are consistent, meaning our results are not sensitive to the distribution used for q_{it}.

Table A1. Sensitivity analysis for distributions of real quality

Quality estimation	Penalty level	Capacity constraints	Random distribution	No review	Adopting review	Adoption decision
Over-estimation	**High**	**Loose**	Uniform	175996	125555	Not Adopt
			Beta(2,2)	175820	125364	Not Adopt
			Beta(3,3)	175981	125351	Not Adopt
			$N(0.5, 0.05^2)$	176047	125486	Not Adopt
			$N(0.5, 0.2^2)$	175975	125629	Not Adopt
		Medium	Uniform	8575	121224	Adopt
			Beta(2,2)	8700	121302	Adopt
			Beta(3,3)	8566	121151	Adopt
			$N(0.5, 0.05^2)$	8452	121139	Adopt
			$N(0.5, 0.2^2)$	8507	121022	Adopt
		Tight	Uniform	-246557	-127788	Adopt
			Beta(2,2)	-246511	-127724	Adopt
			Beta(3,3)	-246618	-127690	Adopt

			$N(0.5, 0.05^2)$	-246522	-127278	Adopt
			$N(0.5, 0.2^2)$	-246669	-127180	Adopt
	Moderate	**Loose**	Uniform	175996	125518	Not Adopt
			Beta(2,2)	175979	125535	Not Adopt
			Beta(3,3)	175963	125286	Not Adopt
			$N(0.5, 0.05^2)$	175924	125465	Not Adopt
			$N(0.5, 0.2^2)$	175972	125640	Not Adopt
		Medium	Uniform	67983	123149	Adopt
			Beta(2,2)	67858	123197	Adopt
			Beta(3,3)	67966	123075	Adopt
			$N(0.5, 0.05^2)$	67997	123102	Adopt
			$N(0.5, 0.2^2)$	68063	123132	Adopt
		Tight	Uniform	-97799	-37746	Adopt
			Beta(2,2)	-97753	-37887	Adopt
			Beta(3,3)	-97718	-38378	Adopt
			$N(0.5, 0.05^2)$	-97775	-38240	Adopt
			$N(0.5, 0.2^2)$	-97783	-38078	Adopt
	Low	**Loose**	Uniform	175854	125460	Not Adopt
			Beta(2,2)	175897	125513	Not Adopt
			Beta(3,3)	175868	125600	Not Adopt
			$N(0.5, 0.05^2)$	175907	125625	Not Adopt
			$N(0.5, 0.2^2)$	175803	126009	Not Adopt
		Medium	Uniform	127500	125020	Not Adopt
			Beta(2,2)	127500	125319	Not Adopt
			Beta(3,3)	127500	125052	Not Adopt
			$N(0.5, 0.05^2)$	127500	125129	Not Adopt
			$N(0.5, 0.2^2)$	127500	125180	Not Adopt
		Tight	Uniform	51000	51000	Indifference
			Beta(2,2)	51000	51000	Indifference
			Beta(3,3)	51000	51000	Indifference
			$N(0.5, 0.05^2)$	51000	51000	Indifference
			$N(0.5, 0.2^2)$	51000	51000	Indifference
Under-estimation	**High**	**Loose**	Uniform	73786	125474	Adopt
			Beta(2,2)	73771	125526	Adopt
			Beta(3,3)	73607	125395	Adopt
			$N(0.5, 0.05^2)$	73871	125380	Adopt
			$N(0.5, 0.2^2)$	73691	125350	Adopt
		Medium	Uniform	73762	121370	Adopt
			Beta(2,2)	73798	121136	Adopt
			Beta(3,3)	73755	121321	Adopt
			$N(0.5, 0.05^2)$	73863	121187	Adopt
			$N(0.5, 0.2^2)$	73748	121307	Adopt
		Tight	Uniform	-8600	-128013	Not Adopt
			Beta(2,2)	-8577	-128052	Not Adopt
			Beta(3,3)	-8596	-126993	Not Adopt
			$N(0.5, 0.05^2)$	-8527	-127359	Not Adopt
			$N(0.5, 0.2^2)$	-8484	-127317	Not Adopt
	Moderate	**Loose**	Uniform	74351	125509	Adopt

		Beta(2,2)	74256	125466	Adopt
		Beta(3,3)	74371	125784	Adopt
		$N(0.5, 0.05^2)$	74268	125615	Adopt
		$N(0.5, 0.2^2)$	74265	125756	Adopt
	Medium	Uniform	74339	123104	Adopt
		Beta(2,2)	74254	123156	Adopt
		Beta(3,3)	74198	123088	Adopt
		$N(0.5, 0.05^2)$	74260	123213	Adopt
		$N(0.5, 0.2^2)$	74312	123151	Adopt
	Tight	Uniform	21287	-38262	Not Adopt
		Beta(2,2)	21241	-38342	Not Adopt
		Beta(3,3)	21175	-38342	Not Adopt
		$N(0.5, 0.05^2)$	21237	-38241	Not Adopt
		$N(0.5, 0.2^2)$	21270	-37773	Not Adopt
Low	**Loose**	Uniform	74716	125609	Adopt
		Beta(2,2)	74816	125564	Adopt
		Beta(3,3)	74849	125648	Adopt
		$N(0.5, 0.05^2)$	74804	125562	Adopt
		$N(0.5, 0.2^2)$	74870	125628	Adopt
	Medium	Uniform	74840	125067	Adopt
		Beta(2,2)	74918	125239	Adopt
		Beta(3,3)	74881	125104	Adopt
		$N(0.5, 0.05^2)$	74805	125141	Adopt
		$N(0.5, 0.2^2)$	74947	125061	Adopt
	Tight	Uniform	50994	51000	Indifference
		Beta(2,2)	50994	51000	Indifference
		Beta(3,3)	50994	51000	Indifference
		$N(0.5, 0.05^2)$	50994	51000	Indifference
		$N(0.5, 0.2^2)$	50994	51000	Indifference

Remark: To make sure the value of q_{it} is within 0 to 1, the normal distribution is truncated between 0 and 1.