Leveraging customer engagement to improve the operational efficiency of social commerce start-ups

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Abstract

Despite the surge of literature on customer engagement (CE) in social media, few studies shed light on how to leverage CE to improve firms' operational efficiency. This research proposes a fresh framework using social media data to improve demand forecasting accuracy, resulting in a cost-efficient inventory control strategy. Drawing upon the resource mobilization perspective in particular, this research quantifies the construct of CE from the view of input-output efficiency evaluation using the Data Envelopment Analysis (DEA) model, and then leverages CE to forecast consumer online demand and reconfigure inventory management strategy. Using a 71-week data set from a social commerce start-up in China, this research shows that this new framework dramatically increases demand forecasting accuracy and reduces operational costs in inventory management. This study contributes to the literature by demonstrating the value of social media data in improving operational efficiency, particularly regarding inventory management.

Keywords: Demand forecasting; Social media; Customer engagement; Inventory management strategy; Resource mobilization

1. Introduction

The exponential growth of social media has generated enormous opportunities for both brick-and-mortar and e-commerce companies to connect with customers, move their businesses onto social media platforms, and become social commerce firms (Aral et al., 2013; Oh et al., 2017; Yan et al., 2018). Both customers and firms can easily engage with each other on social media platforms (Stephen & Toubia, 2010; Ballings & Van den Poel, 2015), which raises the discussion of customer engagement (CE) pertaining to construction (Ho et al., 2020, So et al., 2020), measurement (Shawky et al., 2020), and effect (Simon & Tossan, 2018; Liu et al., 2021). Specifically, based on three distinct levels, including consumption, contribution, and creation, CE is an essential feature of firm-customer communication in social media (Li et al., 2017), through which an individual consumer may have a powerful social influence on firms' selling, promoting, branding, and other marketing activities (Chen et al., 2019).

Thriving social commerce also grants start-ups the opportunity to launch ventures on social media platforms with low entry barriers (Ghezzi et al., 2016). Social commerce start-ups increasingly acknowledge the power of social media in approaching and engaging customers, and the literature emphasizes exploring the antecedents and outcomes of CE (Liu et al., 2021; Ho et al., 2020). However, few studies investigate how these start-ups could optimize their sales and operations planning when confronted with resource constraints and fierce competition. Due to market uncertainty in social commerce (Lam et al., 2019), accurately forecasting customer demands for social commerce operations is particularly challenging for these start-ups that lack the necessary tools to process the rich data available on social media. Moreover, most firms see social media as a new channel of sales, marketing, and communication (Ballings & Van den Poel, 2015), rather than as a source of valuable data for generating operations management insights (Kirac & Milburn, 2018). In this sense, social commerce entrepreneurs and managers tend to identify social media data as too informal and unplanned to support sales and operations management (Bocconcelli et al., 2017), failing to fully mobilize valuable social media resources to foster competitive advantage.

This study aims to help social commerce start-ups leverage social media data for forecasting online demand and reshaping operational strategy, particularly inventory management models. Previous studies have examined the design of social commerce features (Huang & Benyoucef, 2013) and consumer social commerce adoption and use behavior (e.g. Ng, 2013; Liang et al., 2011; Stephen & Toubia, 2010; Chen et al., 2019). Some studies link consumer social media activities to sales performance (Oh et al., 2017; Chong et al., 2016) and equity value (Luo et al., 2013), as well as firm social media activities to firm performance, such as stock returns (Lam et al., 2019; Tirunillai & Tellis, 2012). Many studies have examined the relationship between user-generated content (UGC) from social media and changes in demand, but they neglect demand forecasting accuracy (Schaer et al., 2019). Several studies have started to propose methods using social media to better inform operations management. For instance, Ghezzi et al. (2016) explored the power of unleashing social media for start-up innovation. O'leary (2011) combined social media platforms with radio-frequency identification (RFID) technologies to monitor the movement of goods and improve inventory management. However, very little research has addressed how social commerce start-ups could harness social media data to forecast market changes and support their operational decision-making.

Aiming to close the gaps above, we extend the research of CE in social media into demand forecasting and operational efficiency improvement. We make several contributions to the social media literature and the interface between marketing and operations management. Theoretically, from the perspective of resource mobilization, this study not only links the engagement between social commerce start-ups and their customers in a dynamic manner but proposes an integrated framework to bridge the gap between effective marketing and efficient operations. Specifically, it provides a swift and practicable approach to quantifying CE construct by utilizing Data Envelopment Analysis (DEA), and then synthesizes the quantified variable into the model of online demand forecasting, and ultimately operations planning. Practically, this study asserts that social commerce start-ups can optimize operational performance by integrating CE of social media into their operational planning strategies, especially when those start-ups are confronted with scarce external resources and a fiercely competitive environment.

The structure of this study is organized as follows. We review the relevant literature in order to propose research questions and illustrate our research framework in the next section. Next, we elaborate our research methodology, data, and simulation analysis, and discussion of results. Finally, we conclude with theoretical and managerial implications, and future research directions based on the limitations of this study.

2. Literature review and research question development

2.1. Start-ups in social commerce

Social commerce, defined as an innovative business model of electronic commerce (e-commerce) utilizing Web 2.0 techniques like social media to support business activities

(Han et al., 2018), transforms the e-commerce landscape from a transaction-oriented model into a customer-oriented one. With the prevalence of social media, social commerce extends the relationship between customers and e-vendors pre- and post-transactions online. For example, social commerce firms utilize social media marketing to approach target customers and collect users' feedback via social media embedded tools (Li et al., 2021). Therefore, firms would yield CE in a much more interactive manner by adopting social commerce: customers are not only passive information receivers, but also active firm and brand value co-creators.

The inherent characteristics of social media, such as ease of entry, publicity, and low costs, inspire an expanding number of small and medium enterprises (SMEs), especially start-ups, to get involved in social commerce and boost their business growth. For instance, almost half of SMEs in the U.S. have adopted Facebook to launch their business activities (Wang et al., 2020). Similarly, the WeChat platform in China enables more start-ups to promote and sell their products and services throughout broader social networks (Han et al., 2018). Following this trend, current literature focuses on the effect of social commerce adoption, customer behavior research (Mou & Benyoucef, 2021), and webs and information system design facilitating social commerce processes (Esmaeili & Hashemi G, 2019). However, few studies elucidate how SMEs, particularly start-ups, can use social commerce to improve operational efficiency. We aim to fill in this gap by addressing the two main research questions proposed in this study.

This study follows (Samagaio et al., 2018) to define social commerce start-ups as business entities that first organize and launch their business activities on social media platforms. Confronted with fierce competition and market uncertainty, social commerce start-ups could reshape their operational and decision-making processes to mobilize precious resources via social media channels. For example, social media reduces customer-vendor distance by providing dyadic online communications. Therefore, social commerce start-ups can better understand customer demands and even break into new markets through profound CE. Further, the nature of social media, as the instant communication and networking tool, allows start-ups to optimize decision-making processes by strengthening business relationships and information sharing within and across themselves. However, many social commerce ventures remain skeptical about integrating social media data into their internal operational processes. Decisions based on such information are more likely to be informal and unplanned, and then pose a challenge to successful entrepreneurship without a strategic mindset and a kit of practical tools (Bocconcelli et al., 2017). In this sense, the resource mobilization framework proposed by Drummond et al. (2018) can work as an appealing road map for social commerce start-ups to acquire social media resources and adjust operational processes efficiently. We will develop this theoretical framework after discussing resourceful connotations of CE in social media.

2.2. Customer engagement in social media

Social media enables a firm to promote its presence to a broader network horizon, and engage in multiple conversations with its network actors, including customers, suppliers, retailers, and other stakeholders (Cheng & Krumwiede, 2018). For example, firms and customers engage in dyadic interaction on social media exploiting its inherently diverse modes of expression, such as texts, images, and videos. These enable customers to deliver their feelings, experiences, and expectations toward firms' products or services, thus forming

UGC, which in turn can exert solid and wide-spread influence on other consumers' purchasing decisions (Chen et al., 2019). Many scholars categorize the interaction above under the conceptual label of "customer engagement" (Ho et al., 2020; Liu et al., 2021; Simon & Tossan, 2018; So et al., 2020), and then dynamically dissect this critical notion into distinct dimensions, including consumption (number of views), contribution (number of thumbs-up), and creation (customer comments) (Liu et al., 2021). Current studies on CE focus on its antecedents (Liu et al., 2021), outcomes (Ho et al., 2020), and dynamic management framework (Shawky et al., 2020). Nevertheless, few studies shed light on the transforming effect of CE on firms' operations strategies.

To gain more competitive advantage and benefits by stimulating CE, firms, especially social commerce start-ups, strive to promote their firm-generated content (FGC) across different social media platforms (Alvarez-Milán et al., 2018). FGC efforts, such as tweets, responses to customer comments, and even lucky draw activities, are considered essential for fostering CE (Hautz et al., 2014; Kumar et al., 2016; Viswanathan et al., 2018; Colicev et al., 2019). Even though current research has identified the empowering effect of FGC on UGC, scant literature further investigates the FGC-UGC relationship from an input-output perspective by calculating its productivity. This view is critical because it can navigate these firms relying mainly on social media resources to launch business ventures into harnessing and leveraging CE to improve performance and growth.

When confronted with severe resource constraints, social commerce entrepreneurs start-ups usually focus on boosting CE through personal networks first, after which they seek to develop and maintain CE to further capture market trends, enhance sales, and even break into new markets (Olanrewaju et al., 2020). Although prior studies have achieved consensus on recognizing CE as an external resource for start-ups, the next question is how social commerce start-ups could leverage CE resources to support their internal operational processes. Therefore, regarding the research gaps of CE in social media above, our first research question of this study is as follows:

RQ1: How could social commerce start-ups exploit CE in social media to support their decision-making in operational processes?

2.3. Using social media for resource mobilization

Without CE in social media, firms would risk the loss of both user interaction and vital means of earning customer trust, acquiring problem-solving capabilities, and achieving better performance (Abrahams et al., 2015; Singh et al., 2018; Ho et al., 2020). Considering the significance of social media resources, Drummond et al. (2018) proposed a conceptual framework that guides start-up entrepreneurs in mobilizing social media resources into sales and operations management in a B2B context. In their study, the resource mobilization framework concentrates on social media interactions among different business entities within and across start-ups, and specifies four processes of acquiring, analyzing, and leveraging external resources in social media. Such a framework is compatible with our study as it enables start-ups to explore social media resources by following concrete processes including dyadic and network actor engagement, information search and sharing, collaboration, and operational process coordination and reconfiguration.

However, due to the lack of research utilizing Drummond et al. (2018)'s framework to develop conceptual model in B2C context, we hesitate to adopt the resource mobilization framework. Although prior studies have used this framework to investigate how B2C start-ups use social media to embed themselves in networks (Fraccastoro et al., 2021), these studies neither proposed CE as an essential social media resource, nor took into account social commerce background. Meanwhile, the literature delineates how CE influences sales management rather than operations management, perhaps because social media information seems to be too informal and risky to support operational decision-making (Bocconcelli et al., 2017). Hence, we propose the second research question in this study:

RQ2: Can social commerce start-ups leverage CE in social media to optimize their operations management by following resource mobilization processes?

2.4. Using Resource mobilization theory to develop a research framework

Applying the business network and interaction approach proposed by Industrial Marketing and Purchasing Group, Drummond et al. (2018) formulated a four-process framework demonstrating how entrepreneurial firms could leverage social media to mobilize resources through B2B network development and maintenance. In their original framework, a start-up, with diverse constraints in financial, human, and organizational resources, could promote itself into extensive networks (through dyadic and network actor engagement) and harvest information like market intelligence via social media (information search and sharing). Meanwhile, (collaboration) with business partners could foster high-quality and valuable information flow to eventually penetrate operational processes and achieve highly efficient operations (operational processes coordination and reconfiguration).

Notably, collaboration and operational processes coordination are removed from our research framework due to the scope that we situate this study in the B2C context, which focuses on customers instead of other B2B network actors, such as suppliers or retailers. Figure 1 shows the framework of this study.

--- Figure 1 ---

The first stage of resource mobilization in our framework is the dyadic engagement between start-ups and customers, which is manifested through firm-consumer engagement activities (Kumar et al., 2016; Viswanathan et al., 2018; Liu et al., 2021). By engaging customers in social media, start-ups initially constrained by scarce resources can both broaden their customer network horizon and understand customer needs better and more quickly (Liu et al., 2021). Thus, social media data have significant value for business outcome prediction. For example, social media data have been used to predict sales performance (Oh et al., 2017; Chong et al., 2016), equity value (Luo et al., 2013) and stock performance or returns (Lam et al., 2019; Tirunillai & Tellis, 2012; Bollen et al., 2011). Particularly relevant to this study, Cui et al. (2018) use machine learning models to forecast firm sales from social media data. These studies indicate that CE has a significant impact on online demand; therefore we develop our framework by estimating how efficiently a social commerce start-up could engage with its target customers from an input (FGC)-output (UGC) view.

The second stage of resource mobilization is information searching and sharing. This stage is about interpreting and utilizing information and knowledge flows between start-ups and other network actors, particularly customers in social media (Kaipia et al., 2017). Social media is usually adopted as an effective communication channel between buyers and sellers (Ballings & Van den Poel, 2015). The better a firm understands its customer preferences and purchasing behaviours, the more accurate its demand forecasting can be (Schaer et al., 2019; So et al., 2020). Previous studies in marketing have shown that active CE can significantly affect customer purchasing behavior (Kumar et al., 2016). CE social media data, such as number of views, thumbs-up, products or service reviews representing distinct levels of CE in consumption (least active), contribution (moderately active), and creation (most active), respectively (Liu et al., 2021), can help predict a firm's sales performance (Schaer et al., 2019; Oh et al., 2017; Chong et al., 2016). Thus, after quantifying the variable representing the efficiency of CE from the prior stage, we incorporate this external variable into our demand forecasting model. In this way, we expect that the accuracy of online demand forecasting could be significantly improved.

The last stage of resource mobilization is operational processes reconfiguration. Scholars, including O'leary (2011), Singh et al. (2018), and Drummond et al. (2018), argue that social media promotes the modification of business processes, as well as the updating adaptation of products, processes, and exchanges. At this stage, social commerce start-ups aim to calculate the cost-efficient adjustments of operational processes based on insights generated from timely and accurate demand forecasting. This constitutes an essential foundation for firms' inventory management.

Inventory management is one of the most critical operational processes for both e-commerce and social commerce (Boone et al., 2019). To improve firms' operational efficiency, researchers have incorporated social media data into logistics management research. For instance, O'Leary (2011) combined social media platforms with RFID technologies to monitor the movement of goods throughout the whole supply chain and into inventory management; Flaherty et al. (2012) leveraged Facebook and LinkedIn to identify leads in the B2B sales cycle. However, few studies integrate social media into inventory control and cost reduction modeling to the best of our knowledge. Moreover, fluctuating customer demand spawned by the new social commerce business model do not allow much time for calculating identification (Nemtajela & Mbohwa, 2017), a prevailing challenge requiring firms, especially start-ups, to modify their inventory control strategies to minimize costs. Accordingly, we attempt to reshape and extend the conventional inventory control model by considering the effect of social media.

3. Research methods

3.1. Empirical setting and data collection

An increasing number of start-ups conduct business activities across social media platforms (such as Facebook, Twitter, YouTube, and WeChat). A social commerce start-up's operational procedure can be described as follows: a start-up first posts information on the social media platform about its brand, products, and services, along with customer experience and word-of-mouth, followed by the launch of several business activities, such as promotions, orders, and delivery. Social media users can interact directly with the start-up and other customers to support their purchasing decisions through the same social media platform.

H Company is a social commerce start-up in China, utilizing a WeChat subscription platform (one of the most dominant social media platforms in China) as its channel for product promotion, sales, and order delivery. The core business of H Company is to sell a set of nutritious health products for women. Using its official WeChat subscription platform, the company regularly issues product information and promotions, responds to customer comments and reviews, and organizes lucky draw activities. Customers can access H Company's WeChat shop and complete their purchasing transactions using WeChat Pay.

We collected one of H Company's sales and operations data sets from December 2016 (the time it was founded) to January 2018. Intending to ensure the validity of empirical data in this study, we accessed data from three sources: the internal sales data of H Company, including its products' weekly sales and prices; the public social media data on its WeChat subscription platform, with the authority of H Company; and order delivery status from its collaborative logistics company. To specify the social media data set, we obtained and calculated seven variables for each post, including the date and weekly cumulative number of posts, the content of each post, the number of views, the number of customer reviews, the content of each review, the number of H Company's responses to these reviews, the number of thumbs-up, and the total value of prizes if the post included a lucky draw activity.

In total, we collected data over the course of six on-site visits to H Company. On the first two visits, we presented the current research on social commerce and probed into the business model of H Company. Next, we obtained internal sales and external social media data successively in the 71-week period between the third and fifth visits. On the last visit, we acquired the corresponding logistics data and discussed inventory management further when H Company invited staff from its logistics partner on-site.

3.2. Resource Mobilization (RM) Stage 1: Evaluating customer engagement (CE)

Firms, especially social commerce start-ups, strive to engage with customers through social media, which not only poses a positive effect on their sales improvement, but equips them with a unique channel to interpret customer preferences as well as acquire resources for growth and operations. Specifically, social commerce start-ups' social media efforts, identified as FGC in prior studies, include the number of issued posts per week, the content of each post, the total value of prizes in each lucky draw post, and the number of H Company's responses to customer comments in each post. Correspondingly, CE refers to UGC in social media and entails the number of readings, thumb-ups, and comments regarding each firm-generated post. It is noticeable that start-ups cannot promote unlimited FGCs to chase CE at a high level when confronted with severe resource constraints. Through an input-output perspective to dissect the relationship between FGC and UGC (shown in Table 1), we consider the essential question for social commerce start-ups about how to evaluate the efficiency of acquiring CE with restricted inputs of FGC.

--- Table 1 ---

We employ an input-output DEA model to estimate H Company's efficiency in acquiring customer engagement on the WeChat subscription platform. As a non-parametric linear programming technique, DEA computes firm efficiency and productivity by estimating the distance between data and potential product frontiers, and then allocating optimal weights to multiple input and output variables (Yang & Basile, 2021). DEA has the following advantages over other efficiency estimation methods, such as stochastic frontier analysis (SFA): first, DEA could handle the efficiency-estimating process when firms have multiple inputs and outputs; second, there is no limit to presetting specific forms of production functions when applying DEA method, which turns to be more flexible than SFA; third, DEA measures firm efficiency in a more comprehensive manner by estimating data in each individual peer group.

Furthermore, DEA methods fit our RM theory-based framework by considering H Company's efforts to engage with customers on social media.

There exist two main types of DEA models, input-oriented and output-oriented, respectively. The former focuses on minimizing input variables with the limitation of outputs, while the latter focuses on maximizing outputs with the restricted input items. In this study, an output-oriented DEA model is more adaptive for estimating a social commerce start-up's efficiency in attracting CE, while various resource constraints pose a strain on such social media efforts. We present the specific DEA model below:

$$Max\theta$$

$$Subject \quad to$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} \quad i = 1,2,...m;$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge \theta y_{r0} \quad r = 1,2,...s;$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \ge 0, \quad j = 1,2,...n;$$

In this model, θ represents the efficiency coefficient for the unit under analysis. When this coefficient equals 1, this DMU locates on the production frontier of the DEA model. Otherwise, this DMU is not efficient. x_{ij} and y_{rj} represent the vectors of inputs and outputs, respectively. λ is the vector containing each activity a firm launches.

3.3. RM Stage 2: Integrating CE into online demand forecasting

We combine CE information with an econometric forecasting model based on time series data to forecast the sales of H Company. We refer to our forecasting model as an ARX, as it explains the effects of multiple variables on consumer demand variations. Generally, two components comprise ARX: Autoregressive (AR) and exogenous variables. AR works as the univariate model, and therefore only relies on past sales information to conduct forecasting. Sharing exogenous information besides sales data, ARX improves forecasting accuracy through its multivariate framework to consider extra inputs, such as prices, seasons, and logistics in the context of electronic and social commerce (Schaer et al., 2019). Meanwhile, to delineate the value of CE information in enhancing forecasting accuracy, we also compare forecasting performance between ARX and other univariate models such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA). Exceptionally, if the ARX model integrated with CE information yields better forecasting accuracy performance than others, we could deduce the significance of CE information we have quantified in forecasting online consumer demand for the product of H Company.

The specific analysis procedure of applying ARX consists of three steps: first, selecting and sifting dependent and independent variables from the data set, and then testing the data stationery of each time series variable to avoid pseudo regression; second, establishing ARX model and utilizing a proportion of collected data to examine the coefficients between each selected independent and dependent variables; finally, applying the established ARX model with the rest of data to predict the change of dependent variable. We split the 71-week operational data of H Company into two parts: data from the first 60 weeks for coefficient estimation and the remaining data for demand forecasting. The investigation procedure and analytical outcomes are outlined as follows:

Step 1: Variable selection and data stationary test. Referring to previous online demand analysis studies (Ferreira et al., 2015) and the data fields, we acquired and filtered out the dependent variables, weekly customer online demands, and independent variables per week, e.g. lagged online customer demand representing autoregression of time series data (Boone et al., 2017), product prices (Chong et al., 2016), order delivery state, seasons moderating factor and CE. Among these variables, product price refers to the actual prices of customer purchasing rather than product label prices; order delivery and season moderating factors are two dummy variables, representing the Spring Festival logistics outage and different seasons, respectively. The specific ARX model equation is as follows:

$$\ln D_t = \beta_0 + \beta_1 \ln D_{t-1} + \beta_2 \text{Price}_{\text{t}} + \beta_3 \text{Springfestival}_{\text{t}} + \beta_4 \text{Seasonfactor}_{\text{t}} + \beta_5 \text{CE}_{\text{t}}$$

Step 2: Variable coefficients estimation. We ran the ARX model for estimating variable coefficients by using operational data from the first 60 weeks. To avoid heteroscedasticity caused by various variable measurement units, we took the logarithmic form of customer online demand data.

Step 3: Forecasting accuracy comparison across different models. We compared forecasting accuracy among different time series analysis models, including ARX with CE, ARX without CE, ARIMA, and MA; the latter two have been widely used in industry (Petropoulos et al., 2019). Following Ramos et al. (2015), we compared the forecasting accuracy of different models from three facets of error, including Root Mean Square Error

(RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

3.4. RM Stage 3: Reconfiguring inventory management strategy

As the third process of RM, reconfiguring the operational processes aims to ease enterprises' burden by reducing operational costs, especially for those start-ups with constrained resources, like H Company. Accurate demand forecasting reduces inventory costs (Barrow & Kourentzes, 2016). Hence, the order up to (OUT) level policy for inventory should combine demand forecasting with inventory replenishment decisions (Teuntera & Babai, 2010; Babaiabcc, 2011).

As presented in Figure 1, the conventional inventory management decision process includes three steps: first, forecasting demand in each period; then, calculating the minimized costs based on the predicted demand, and determining the OUT level in each period; finally, estimating the optimal order quantity in each period. This conventional inventory management process has been widely used in manufacturing industries (Petropoulos et al., 2019). However, the competition is much more intense in the context of social commerce. The start-ups (e.g. H Company) must quickly seize potential sales opportunities and meet the fluctuating online demand. They cannot afford to follow the conventional routine of inventory management and planning. Therefore, we propose an integrated inventory management decision process, as shown in Figure 2. We integrate ARX with the CE model into the inventory control policy in much longer N periods, which can directly decide OUT levels in N periods rather than finishing the step period by period; after that, the optimal order quantity can be calculated.

--- Figure 2 ---

There are two main perceived benefits for the integrated inventory management decision process compared to the conventional process. First, it enables social commerce start-ups to save the decision-making time of inventory management by simplifying processes. Second, we propose that the integrated inventory management model can enhance start-ups' operational efficiency by reducing inventory costs. Accordingly, we applied a simulation-based analysis of the H Company inventory cost between the conventional inventory management decision process and the integrated one across three scenarios. The results from such simulation analysis should be optimal within one or several weeks. However, an annual demand estimation should yield suboptimal results, given that intense competition and demand uncertainty propel social commerce start-ups to react to consumer orders swiftly within one or several periods instead of a year. We expect the total inventory costs of the integrated inventory management strategy to be much lower than the conventional one.

3.4.1. Components of H Company's inventory costs and scenario settings

In accordance with the stock position and online order forecasting, H Company organizes production weekly and keeps production costs at a comparatively stable level. Thus, we assume that production costs do not influence inventory costs. The total inventory costs are comprised of the holding cost of maintaining product inventory levels and product transhipping, and the shortage cost incurred when products are sold out or the stock cannot meet customer demand. According to H Company's operational real-time data, the per product holding cost is relatively fixed at 5 (unit: RMB), whereas the shortage cost is uncertain and varies in different situations. Thus, analyzing the total inventory costs is complicated.

We set up three scenarios to specify the effect of an ambiguous shortage cost on total inventory costs by increasingly extending the range of the shortage cost. In the first scenario, we assume that the shortage cost equals the holding cost as H Company can transfer stocks swiftly from its factory into its inventory. In the second scenario, each product shortage cost is supposed to equal sales profit (20 RMB) because H Company loses a sales opportunity to earn profit on this unit in the competitive social commerce market. In the last scenario, we set the shortage cost per product up to 50 (unit: RMB), including unit profit and the cost of attracting customers. Tor the reason, H Company not only loses unit profit, but also pays the cost of failing to attract a customer to buy via social media.

3.4.2. Inventory cost analysis

With the principal goal of minimizing total inventory costs (the sum of holding and shortage costs), we adopted a simulated annealing algorithm (SAA)-based inventory analysis method to run H Company's weeks 61-71 operational data in the three different scenarios. SAA was originated from simulating the minimum time spent when firefighters endeavored to put out a forest fire. Previous studies showed SAA as a practical and efficient algorithm to calculate the minimum of object function (Bouleimen & Lecocq, 2003; Rodriguez-Tello et al., 2008; Goodson, 2015). We conducted the analysis using Spyder 3.2 with Python 3.6.

4. Results

4.1. Measuring CE

Pearson correlation analysis was run to test whether FGC input and UGC output variables meet the basic homotropy assumption. The results of the analysis are shown in Table 2.

--- Table 2 ---

The results show that all the UGC output variables have positive correlations with FGC input ones, satisfying the basic homotropy assumption. Therefore, we used DEAP 2.1, a professional DEA-based computing software, to evaluate the social engagement between FGC input and UGC output, and the results are presented in Table 3.

--- Table 3 ---

H Company issued posts on its WeChat subscription platform in 49 out of 71 weeks from October 2016 to January 2018. The DEA method compresses the efficiency evaluation results, θ, in a range from 0 to 1, which means 100% input loss and 0% input loss compared with the output figures. Each CE evaluated results in these 49 weeks range from the minimum of 0.555 to the maximum of 1, with an average of 0.784.

4.2. ARX-based time series analysis

Step 1: The results of the data stationary test. As the only time series variable, customer online demand was tested for data stationary through an ADF unit root test (Z(t) statistics = -5.262 < 1% significant ADF statistics = -4.106), and test results demonstrate this variable should be one order lagged (one order lagged auto-correlation coefficient = 0.4165*** with p value = 0.0003, two orders lagged auto-correlation coefficient=0.0917 with p value=0.0762), determining the subscript of customer online demand as t-1 when acting as independent part for depicting time series autoregression. The specific meaning, data type, and the basis of the selection of each variable are listed in Table 4.

--- Table 4 ---

Step 2: Variable coefficients estimation. Table 4 shows the estimated results. The estimated coefficient between CE and logarithmic online demand is 0.760. Besides, the one order lagged logarithmic online demand coefficient, illustrating consumer purchasing inertia (Boone et al., 2017), is estimated to be lower than CE. The season moderating factor does not seem to be significantly positive with online demand. This is because H Company's sales data contains only one type of female health product, which is consumed throughout the year, irrespective of season.

The estimated coefficients of price and logistical outages during the Chinese Spring Festival are both negatively correlated with online demand, which is consistent with the reality: customers are sensitive to product prices, especially those of nutritious health products, and will not purchase products online when delivery of goods stops offline.

ARX model explains the fluctuation of online demand better than AR model, with adjusted R^2 increasing from 16.16% to 62.75%. Adding CE as an exogenous explaining factor, the ARX model shows a nearly 10% improvement in the interpretation of online demand variance than the previous one without CE.

Step 3: Forecasting accuracy comparison. We separately run the models on H Company's last 11 weeks of operational data using different models. The results are presented in Table 5.

--- Table 5 ---

The results indicate that the ARX model synthesized with CE yields the best forecasting accuracy with the minimum forecast error in RMSE, MAE, and MAPE. The lowest MAPE is 27.7% of the ARX model with CE, followed by 39.9% of the ARX model without CE, 46.3% of ARIMA, and 60.2% of MA. On the whole, the two multivariate ARX forecasting models outperform the univariate ones. Focusing solely on the variation of time series data cannot achieve satisfactory forecasting results compared with multivariate models. Although the MAPE of ARX with CE is still 27.7%, the forecasting accuracy of this model outweighs the counterparts of any other univariate forecasting models and even increases 10% compared to ARX without CE information. Based on these results, we can confirm the value of CE in enhancing the demand forecasting accuracy of H Company.

4.3. Inventory cost analysis

The results of the SAA-based inventory are shown in Figure 3. The blue line with the triangle icon represents total inventory costs of conventional inventory management strategy, and the red line with a circle icon represents the counterpart of integrated inventory management strategy. Holding costs and shortage costs are represented by H and W, respectively. In all three scenarios, the blue line is always higher than the red line, suggesting that the total inventory costs originating from the conventional strategy are always higher than those from the integrated strategy. Moreover, differences in total inventory costs between these two strategies gradually widen, increasing the shortage cost from Scenario 1 to Scenario 3. The results confirm that the integrated inventory management strategy we proposed drastically reduces the firm's total inventory costs compared with the conventional strategies.

--- Figure 3 ---

In sum, the results of the analysis confirm that social commerce start-ups could leverage CE to enhance operational efficiency by appropriately mobilizing such a social media resource into their sales and operational planning. CE helps start-ups forecast online demand more accurately and then reconfigure inventory management model to reduce costs. Therefore, efficient operations can be achieved when a start-up acquire more social media resources and lowers its inventory management costs.

5. Discussion and conclusion

Following the potential mechanism of using social media to achieve performance improvement, most recent studies illustrate the power of social media in combination with particular operational planning processes, including demand forecasting (Cui et al., 2018), logistics monitoring (Kirac & Milburn, 2018), and supplier identification (Banerjee et al., 2020). While current literature in electronic commerce emphasizes the adoption effect of social commerce, consumer behavior, and information system design, few studies investigate how social commerce firms, especially start-ups with resource constraints, could leverage social media to optimize their sales and operations management. In this study, we argue that social commerce start-ups can exploit CE in social media, an essential external resource for start-ups (Drummond et al., 2018; Ho et al., 2020; Shawky et al., 2020; So et al., 2020), to reduce inventory cost and then enhance operational efficiency.

Timely and accurate consumer demand forecasting is a prerequisite for social commerce operations planning, as is inventory management, in particular (Ramanathan et al., 2017; Boone et al., 2019). This study proposes a framework for start-ups in social commerce to harness CE data in social media, mobilizing resources that are vital for business growth and development, to align operations planning processes, including the improvement of demand forecasting accuracy and the reduction of inventory costs. Thus, we contribute to social media and business research literature, and this contribution has several managerial implications.

5.1. Theoretical contributions

First, as one of the most effective channels for directly communicating and engaging with customers, social media enables start-ups in social commerce to not only boost sales by interpreting customers' demand interactively but integrate external resources into internal operational processes. While many researchers have examined the impact of social media on firms' operational performance (Lam et al., 2016; Schmidt et al., 2020; Wang et al., 2020), little is known about the specific mechanism of how firms, especially social commerce start-ups, could utilize social media to optimize operational processes. Guided by RM theory, our findings unpack the operational value of CE on social media by dividing the resource integration process into three specific stages, and ultimately achieving the improvement of demand forecasting accuracy and operational cost reduction. Therefore, this study contributes to CE research in social media by providing a new conceptual framework to explore marketing and operations management interfaces.

Second, following Liu et al. 's (2019) work, we further quantify CE from the perspective of its development process. Firms, particularly start-ups, in social commerce are prone to CE in social media by posting tweets, responding to reviews, arranging activities, etc. Such social media efforts will stimulate customer behaviors, including consumption (number of views), contribution (number of thumbs-up), and creation (comments), which comprise distinct dimensions of CE (Muntinga et al., 2011). As the literature has abundantly explored and discussed the business value of CE, this study integrates a start-up's efforts with CE outcomes in social media to measure its dynamic CE capability by employing an input-output efficiency evaluation approach, namely, the DEA model. Following RM theory, we then apply this quantified CE to forecast online demand and reconfigure inventory management strategy. This study shows the result of improving forecasting accuracy and substantially reducing operational costs in, underscoring the potential of CE in sales and operations planning research.

Third, this study illustrates the power of combining empirical analysis with simulation method for demand forecasting and operations planning. We derive empirical analysis results from a single case and apply these insights to several scenarios through simulation (Stauffer et al., 2018). The case illustration shows that such a combined approach of integrating CE can substantially improve online demand forecasting accuracy. Thus, unlike many previous studies that only relied on utilizing UGC to forecast demand, we open up avenues for both marketing and operations management scholars to incorporate CE data in social media. Furthermore, the inventory cost analysis results suggest that the cost reduction achieved through integrated inventory control strategy across three different scenarios surpasses that of conventional inventory control strategy. These findings contribute to the prior studies on bridging the separate but independent relationship between demand forecasting and inventory management (Syntetos et al., 2015), and show the integration between demand forecasting and operations processes on improving operational efficiency.

5.2. Managerial implications

First, we accentuate the significance of CE as an essential social media resource in supporting the sales and operational planning of social commerce start-ups. Although prior studies acknowledged the effect of such a resource upon start-ups' sales processes and reputation management (Tajvidi et al., 2020), social commerce companies, especially start-ups, avoid basing operational plannings on social media data in terms of its informal, random, and hard-to-quantify features. We illustrate the value of CE in improving sales forecasting accuracy and reducing inventory cost through H Company case, which other social commerce start-ups could adopt. For example, social commerce entrepreneurs and managers should devote more effort to designing communication content and patterns via social media to engage with target customers, so that they are better able to capture market changes and then optimize their operational processes.

Second, the research framework proposed in our study can equip start-up managers with a strategic mindset for exploiting social media resources efficiently. The ability to do so depends on the features and specific strategies of social commerce start-ups. With this in mind, we develop a framework that illustrates the stages of mobilizing social media resources to address resource constraints; the framework enables start-up managers to cultivate strategies to allocate these resources to sales and operations management. For instance, a social commerce start-up could assign a manager responsible for handling and sharing social media information to facilitate sales and operations processes.

Plenty of barriers prevent managers from thinking more strategically about how to leverage social media data to improve sales and operations without appropriate approaches. Therefore, the third implication of this study is provides social commerce managers with grouping approaches for quantifying and utilizing CE in sales and operations management to implement complementary social media strategies. For example, managers could use CE to achieve better forecasting accuracy by following a multivariate method. Meanwhile, sharing social media information among departments effectively and in a timely manner as designed in this study could reduce costs, thereby improving operational efficiency.

5.3. ***Limitations and future research directions***

Like other research in the same domain, our study has certain limitations. Future research could get a more comprehensive picture of exploring and understanding the impact of CE on business process modification by addressing the following limitations.

First, the research context of this study only focuses on one social commerce start-up in China, which constrains our findings and conclusions to a Chinese context. Future research could further explore how these start-ups or other business entities in different contexts apply social media strategies to optimize their operational planning. Moreover, even though this study utilized a data set containing external social media and internal operations data, just one start-up from one social media platform cannot illustrate the whole picture of social commerce, especially when more and more players are joining in this game-changing e-commerce field. Therefore, future studies may reveal more insight into the impact of social media on operations management by enlarging the sampling sources across different social media platforms.

Second, we followed Liu et al. (2019) to measure CE in social media. However, as a prevailing topic in social media and marketing management, CE has been developing and evolving in terms of conceptualization and measurement in recent years. Hence, future studies could interpret this essential construct from diverse perspectives and then unleash the potential of CE to support the decision-making process of firms' operational planning and achieve better performance.

Third, in the stage of demand forecasting, we followed the specific guidelines in the Golden Rules of Forecasting (Armstrong et al., 2015) and carefully selected the moderators from the existing demand forecasting literature. This may risk leaving out some crucial variables, such as product return rate, which may impact on demand forecasting in turn (Brito & Laanb, 2009; Li et al., 2016; Yan & Cao, 2017; Zhang et al., 2018). In this study, product return data are not available for H Company, which sells consumable, rather than durable products. Meanwhile, Chinese consumers are more likely to regard product return as time-consuming and a nuisance due to a more strict return policy and less advanced reverse logistics, especially when compared with developed countries such as the U.S. (Janakiraman et al., 2016). Hence, consumers would be unlikely to return these products after having consumed them, and H Company did not provide its product return data for us. Future studies in forecasting social commerce demand could take product return into consideration as an essential factor.

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References

ABRAHAMS, A. S., FAN, W., WANG, G. A., ZHANG, Z. & JIAO, J. 2015. An Integrated Text Analytic Framework for Product Defect Discovery. *Production & Operations Management,* 24**,** 975-990.

ALVAREZ-MILáN, A., FELIX, R., RAUSCHNABEL, P. A. & HINSCH, C. 2018. Strategic customer engagement marketing: A decision making framework. *Journal of Business Research,* 92**,** 61-70.

ARAL, S., DELLAROCAS, C. & GODES, D. 2013. Introduction to the special issue—social media and business transformation: a framework for research. *Information Systems Research,* 24**,** 3-13.

ARMSTRONG, J. S., GREEN, K. C. & GRAEFE, A. 2015. Golden rule of forecasting: Be conservative. *Journal of Business Research,* 68**,** 1717-1731.

BABAIABCC, M. Z. 2011. Analysis of order-up-to-level inventory systems with compound Poisson demand. *European Journal of Operational Research,* 210**,** 552-558.

BALLINGS, M. & VAN DEN POEL, D. 2015. CRM in social media: Predicting increases in Facebook usage frequency. *European Journal of Operational Research,* 244**,** 248-260.

BANERJEE, A., RIES, J. M., WIERTZ, C. J. I. J. O. O. & MANAGEMENT, P. 2020. The impact of social media signals on supplier selection: insights from two experiments. *International Journal of Operations & Production Management*, 40 (5):531-552

BARROW, D. K. & KOURENTZES, N. 2016. Distributions of forecasting errors of forecast combinations: Implications for inventory management. *International Journal of Production Economics,* 177**,** 24-33.

BO, W. & SHEN, H. 2015. Analyzing and predicting news popularity on Twitter. *International Journal of Information Management,* 35**,** 702-711.

BOCCONCELLI, R., CIOPPI, M. & PAGANO, A. 2017. Social media as a resource in SMEs' sales process. *Journal of Business and Industrial Marketing,* 32**,** 693-709.

BOLLEN, J., MAO, H. & ZENG, X. 2011. Twitter mood predicts the stock market. *Journal of Computational Science,* 2**,** 1-8.

BOONE, T., GANESHAN, R., HICKS, R. L. & SANDERS, N. R. 2017. Can Google Trends Improve your Sales Forecast? *Production & Operations Management,* 27**,** 1770-1774.

BOONE, T., GANESHAN, R., JAIN, A. & SANDERS, N. R. 2019. Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting,* 35**,** 170-180.

BOULEIMEN, K. & LECOCQ, H. 2003. A new efficient simulated annealing algorithm for the resource-constrained project scheduling problem and its multiple mode version. *European Journal of Operational Research,* 149**,** 268-281.

BRITO, M. P. D. & LAANB, E. A. V. D. 2009. Inventory control with product returns: The impact of imperfect information. *European Journal of Operational Research,* 194**,** 85-101.

CHEN, Z.-Y., FAN, Z.-P. & SUN, M. 2019. Individual-level social influence identification in social media: A learning-simulation coordinated method. *European Journal of Operational Research,* 273**,** 1005-1015.

CHENG, C. C. J. & KRUMWIEDE, D. 2018. Enhancing the performance of supplier

involvement in new product development: the enabling roles of social media and firm capabilities. *Supply Chain Management,* 23**,** 171-187.
CHONG, A., LI, B., NGAI, E., CH'NG, E. & LEE, F. 2016. Predicting online product sales via online reviews, sentiments, and promotion strategies: a big data architecture and neural network approach. *International Journal of Operations & Production Management,* 36**,** 358-383.
COLICEV, A., KUMAR, A. & O'CONNOR, P. 2019. Modelling the relationship between firm and user generated content and the stages of the marketing funnel. *International Journal of Research in Marketing,* 36**,** 100-116.
CUI, R., GALLINO, S., MORENO, A. & ZHANG, D. J. 2018. The Operational Value of Social Media Information. *Production and Operations Management,* 27**,** 1749-1769.
DRUMMOND, C., MCGRATH, H. & O'TOOLE, T. 2018. The impact of social media on resource mobilisation in entrepreneurial firms. *Industrial Marketing Management,* 70**,** 68-89.
ESMAEILI, L. & HASHEMI G, S. A. 2019. A systematic review on social commerce. *Journal of Strategic Marketing,* 27**,** 317-355.
FERREIRA, K. J., LEE, B. H. A. & SIMCHI-LEVI, D. 2015. Analytics for an online retailer: Demand forecasting and price optimization. *Manufacturing & Service Operations Management,* 18**,** 69-88.
FINCH, J., WAGNER, B. & HYNES, N. 2012. Resources prospectively: How actors mobilize resources in business settings. *Journal of Business Research,* 65**,** 164-174.
FLAHERTY, K., LAM, S. K., LEE, N., MULKI, J. P. & DIXON, A. L. 2012. Social Network Theory and the Sales Manager Role: Engineering the Right Relationship Flows. *Journal of Personal Selling & Sales Management,* 32**,** 183-192.
FRACCASTORO, S., GABRIELSSON, M. & CHETTY, S. 2021. Social Media Firm Specific Advantages as Enablers of Network Embeddedness of International Entrepreneurial Ventures. *Journal of World Business,* 56.
GHEZZI, A., GASTALDI, L., LETTIERI, E., MARTINI, A. & CORSO, M. 2016. A role for start-ups in unleashing the disruptive power of social media. *International Journal of Information Management,* 36**,** 1152-1159.
GOH, K.-Y., HENG, C.-S. & LIN, Z. 2013. Social media brand community and consumer behaviour: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research,* 24**,** 88-107.
GOODSON, J. C. 2015. A priori policy evaluation and cyclic-order-based simulated annealing for the multi-compartment vehicle routing problem with stochastic demands. *European Journal of Operational Research,* 241**,** 361-369.
HAUTZ, J., FüLLER, J., HUTTER, K. & THüRRIDL, C. 2014. Let users generate your video ads? The impact of video source and quality on consumers' perceptions and intended behaviours. *Journal of Interactive Marketing,* 28**,** 1-15.
HAN, H., XU, H. & CHEN, H. 2018. Social commerce: A systematic review and data synthesis. *Electronic Commerce Research and Applications,* 30**,** 38-50.
HITE, J. M. 2010. Evolutionary processes and paths of relationally embedded network ties in emerging entrepreneurial firms. *Entrepreneurship Theory & Practice,* 29**,** 113-144.
HO, M. H. W., CHUNG, H. F. L., KINGSHOTT, R. & CHIU, C. C. 2020. Customer

engagement, consumption and firm performance in a multi-actor service eco-system: The moderating role of resource integration. *Journal of Business Research*,121,557-566

HUANG, Z. & BENYOUCEF, M. 2013. From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications,* 12**,** 246-259.

JANAKIRAMAN, N., SYRDAL, H. A. & FRELING, R. 2016. The Effect of Return Policy Leniency on Consumer Purchase and Return Decisions: A Meta-analytic Review. *Journal of Retailing,* 92**,** 226-235.

KAIPIA, R., HOLMSTRöM, J., SMåROS, J. & RAJALA, R. 2017. Information sharing for sales and operations planning: Contextualized solutions and mechanisms. *Journal of Operations Management,* 52**,** 15-29.

KIRAC, E. & MILBURN, A. B. 2018. A general framework for assessing the value of social data for disaster response logistics planning. *European Journal of Operational Research,* 269**,** 486-500.

KUMAR, A., BEZAWADA, R., RISHIKA, R., JANAKIRAMAN, R. & KANNAN, P. 2016. From social to sale: The effects of firm-generated content in social media on customer behaviour. *Journal of Marketing,* 80**,** 7-25.

LAM, H. K. S., YEUNG, A. C. L. & CHENG, T. C. E. 2016. The impact of firms' social media initiatives on operational efficiency and innovativeness. *Journal of Operations Management,* 47-48**,** 28-43.

LAM, H. K. S., YEUNG, A. C. L., LO, C. K. Y. & CHENG, T. C. E. 2019. Should firms invest in social commerce? An integrative perspective. *Information & Management***,** doi: 10.1016/j.im.2019.04.007.

LEE, Y. H. & QIU, C. 2009. When Uncertainty Brings Pleasure: The Role of Prospect Image ability and Mental Imagery. *Journal of Consumer Research,* 36**,** 624-633.

LI, C.-Y. & KU, Y.-C. 2018. The power of a thumbs-up: Will e-commerce switch to social commerce? *Information & Management,* 55**,** 340-357.

LI, F., LARIMO, J. & LEONIDOU, L. C. 2021. Social media marketing strategy: definition, conceptualization, taxonomy, validation, and future agenda. *Journal of the Academy of Marketing Science,* 49**,** 51-70.

LI, S., ZHENG, R. & LI, L. B. 2007. Do shared features of offered alternatives have an effect in consumer choice? *Journal of Economic Psychology,* 28**,** 658-677.

LI, Y., LUO, P., FAN, Z.-P., CHEN, K. & LIU, J. 2017. A utility-based link prediction method in social networks. *European Journal of Operational Research,* 260**,** 693-705.

LI, Z., XIE, J., GU, X., YONG, L., IEROMONACHOU, P. & ZHANG, X. 2016. Forecasting return of used products for remanufacturing using Graphical Evaluation and Review Technique (GERT). *International Journal of Production Economics*, 181**,** 315-324.

LIANG, T.-P., HO, Y.-T., LI, Y.-W. & TURBAN, E. 2011. What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce,* 16**,** 69-90.

LIU, X., SHIN, H. & BURNS, A. C. 2021. Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing. *Journal of Business R*esearch, 125, 815-826.

LOCKETT, A., SIEGEL, D., WRIGHT, M. & ENSLEY, M. D. 2005. The creation of spin-off

firms at public research institutions: Managerial and policy implications. *Research Policy,* 34**,** 981-993.
LUO, X., ZHANG, J. & DUAN, W. 2013. Social media and firm equity value. *Information Systems Research,* 24**,** 146-163.
MAHDILOO, M., JAFARZADEH, A. H., SAEN, R. F., TATHAM, P. & FISHER, R. 2016. A multiple criteria approach to two-stage data envelopment analysis. *Transportation Research Part D,* 46**,** 317-327.
MOU, J. & BENYOUCEF, M. 2021. Consumer behaviour in social commerce: Results from a meta-analysis. *Technological Forecasting and Social Change,* 167.
MUNTINGA, D. G., MOORMAN, M. & SMIT, E. G. 2011. Introducing COBRAs: Exploring motivations for Brand-Related social media use. *International Journal of Advertising,* 30(1),13-46.
NEMTAJELA, N. & MBOHWA, C. 2017. Relationship between Inventory Management and Uncertain Demand for Fast Moving Consumer Goods Organisations. *Procedia Manufacturing,* 8**,** 699-706.
NG, C. S.-P. 2013. Intention to purchase on social commerce websites across cultures: A cross-regional study. *Information & Management,* 50**,** 609-620.
NISAR, T. M. & PRABHAKAR, G. 2018. Trains and Twitter: Firm generated content, consumer relationship management and message framing. *Transportation Research Part A: Policy and Practice,* 113**,** 318-334.
OLANREWAJU, A. S. T., HOSSAIN, M. A., WHITESIDE, N. & MERCIECA, P. 2020. Social media and entrepreneurship research: A literature review. *International Journal of Information Management,* 50**,** 90-110.
O'LEARY, D. E. 2011. The use of social media in the supply chain: survey and extensions. *Intelligent Systems in Accounting, Finance and Management,* 18**,** 121-144.
OH, C., ROUMANI, Y., NWANKPA, J. K. & HU, H.-F. 2017. Beyond likes and tweets: Consumer engagement behaviour and movie box office in social media. *Information & Management,* 54**,** 25-37.
PETROPOULOS, F., WANG, X. & DISNEY, S. M. 2019. The inventory performance of forecasting methods: Evidence from the M3 competition data. *International Journal of Forecasting,* 35**,** 251-265.
PRENDERGAST, G. P. & THOMPSON, E. R. 2010. Sales promotion strategies and belief in luck. *Psychology & Marketing,* 25**,** 1043-1062.
RAMANATHAN, U., SUBRAMANIAN, N. & PARROTT, G. 2017. Role of social media in retail network operations and marketing to enhance customer satisfaction. *International Journal of Operations & Production Management,* 37**,** 105-123.
RAMOS, P., SANTOS, N. & REBELO, R. 2015. Performance of state space and ARIMA models for consumer retail sales forecasting. *Robotics and Computer-Integrated Manufacturing,* 34**,** 151-163.
RODRIGUEZ-TELLO, E., HAO, J.-K. & TORRES-JIMENEZ, J. 2008. An improved simulated annealing algorithm for bandwidth minimization. *European Journal of Operational Research,* 185**,** 1319-1335.
SAMAGAIO, A., CRESPO, N. F. & RODRIGUES, R. 2018. Management control systems in high-tech start-ups: An empirical investigation. *Journal of Business Research,* 89**,**

351-360.

SCHAER, O., KOURENTZES, N. & FILDES, R. 2019. Demand forecasting with user-generated online information. *International Journal of Forecasting,* 35**,** 197-212.

SCHMIDT, C. G., WUTTKE, D. A., BALL, G. P. & HEESE, H. S. 2020. Does social media elevate supply chain importance? An empirical examination of supply chain glitches, Twitter reactions, and stock market returns. *Journal of Operations Management,* 66**,** 646-669.

SHAWKY, S., KUBACKI, K., DIETRICH, T. & WEAVEN, S. 2020. A dynamic framework for managing customer engagement on social media. *Journal of Business Research,* 121**,** 567-577.

SIMON, F. & TOSSAN, V. 2018. Does brand-consumer social sharing matter? A relational framework of customer engagement to brand-hosted social media. *Journal of Business Research,* 85**,** 175-184.

SINGH, A., SHUKLA, N. & MISHRA, N. 2018. Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review,* 114**,** 398-415.

SO, K. K. F., WEI, W. & MARTIN, D. 2020. Understanding customer engagement and social media activities in tourism: A latent profile analysis and cross-validation. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.05.054

STAUFFER, J. M., PEDRAZA-MARTINEZ, A. J., YAN, L. L. & VAN WASSENHOVE, L. N. 2018. Asset supply networks in humanitarian operations: A combined empirical-simulation approach. *Journal of Operations Management,* 63**,** 44-58.

STEPHEN, A. T. & TOUBIA, O. 2010. Deriving value from social commerce networks. *Journal of marketing research,* 47**,** 215-228.

SWANI, K., BROWN, B. P. & MILNE, G. R. 2014. Should tweets differ for B2B and B2C? An analysis of Fortune 500 companies' Twitter communications. *Industrial marketing management,* 43**,** 873-881.

SYNTETOS, A. A., ZIED BABAI, M. & GARDNER, E. S., JR. 2015. Forecasting intermittent inventory demands: Simple parametric methods vs. bootstrapping. *Journal of Business Research,* 68**,** 1746-1752.

TAJVIDI, M., RICHARD, M. O., WANG, Y. & HAJLI, N. 2020. Brand co-creation through social commerce information sharing: The role of social media. *Journal of Business Research,* 121**,** 476-486.

TEUNTERA, R. H. & BABAI, M. Z. 2010. Determining order-up-to levels under periodic review for compound binomial (intermittent) demand. *European Journal of Operational Research,* 203**,** 619-624.

THIES, C., KIECKHäFER, K., SPENGLER, T. S. & SODHI, M. S. 2019. Operations research for sustainability assessment of products: A review. *European Journal of Operational Research,* 274**,** 1-21.

TIRUNILLAI, S. & TELLIS, G. J. 2012. Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science,* 31**,** 198-215.

VISWANATHAN, V., MALTHOUSE, E. C., MASLOWSKA, E., HOORNAERT, S. & VAN DEN POEL, D. 2018. Dynamics between social media engagement, firm-generated content, and live and time-shifted TV viewing. *Journal of Service Management,* 29**,**

378-398.
WANG, Y., ZHANG, M., TSE, Y. K. & CHAN, H. K. 2020. Unpacking the impact of social media analytics on customer satisfaction: do external stakeholder characteristics matter? *International Journal of Operations and Production Management,* 40**,** 647-669.
WANG, X., TAJVIDI, M., LIN, X. & HAJLI, N. 2020. Towards an Ethical and Trustworthy Social Commerce Community for Brand Value Co-creation: A trust-Commitment Perspective. *Journal of Business Ethics,* 167**,** 137-152.
YAN, R. & CAO, Z. 2017. Product returns, asymmetric information, and firm performance. *International Journal of Production Economics*, 185**,** 211-222.
YAN, W., XIONG, Y., CHU, J., LI, G. & XIONG, Z. 2018. Clicks versus Bricks: The role of durability in marketing channel strategy of durable goods manufacturers. *European Journal of Operational Research,* 265**,** 909-918.
YANG, J. & BASILE, K. 2021. Communicating Corporate Social Responsibility: External Stakeholder Involvement, Productivity and Firm Performance. *Journal of Business Ethics*.
ZHANG, L. H., LI, T. & FAN, T. J. 2018. Inventory misplacement and demand forecast error in the supply chain: profitable RFID strategies under wholesale and buy-back contracts. *International Journal of Production Research***,** 1-18.

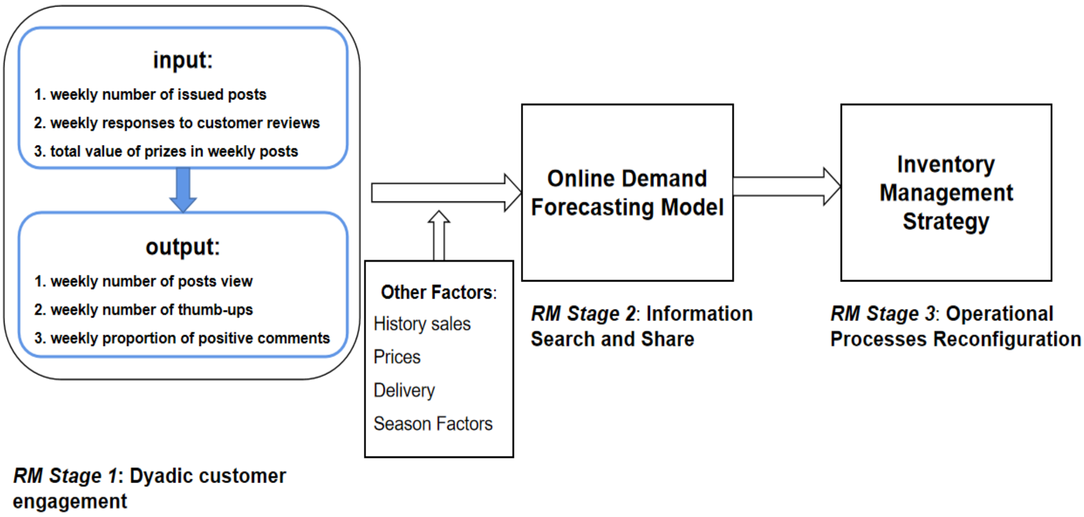

Figure 1. The research framework

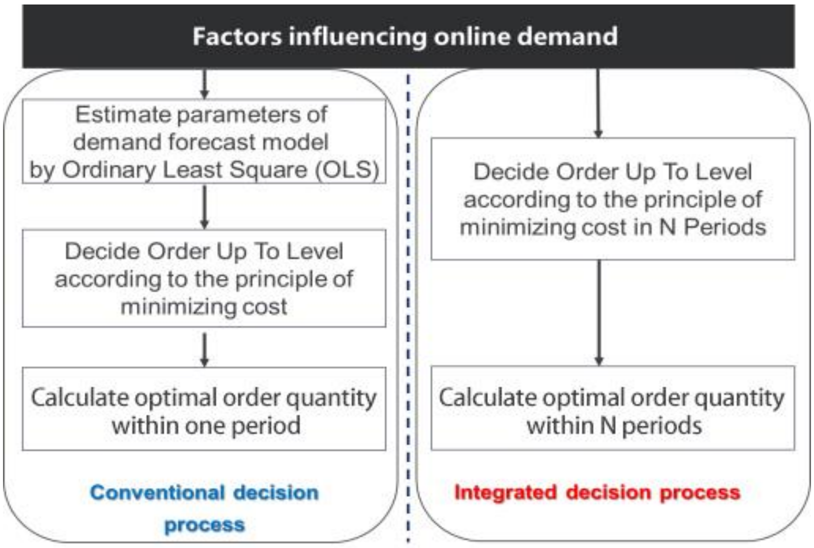

Figure 2. Comparison of the conventional and integrated inventory management decision processes

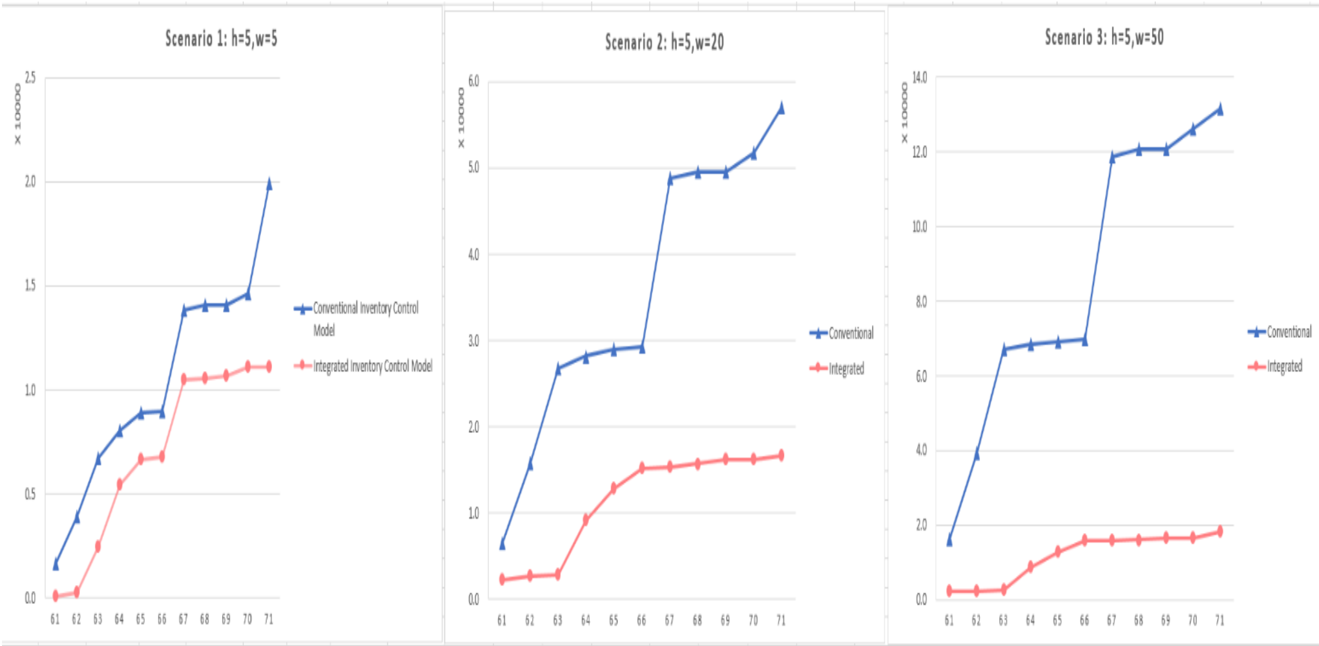

Figure 3. Comparison of total inventory costs for conventional and integrated inventory control strategies in three scenarios

Table 1. The input and output variables extracted from FGC and UGC

Input/output Variables	Definition	Reference
	Firm-generated content	
The weekly number of issued posts	The number of posts H Company has issued per week	Tirunillai and Tellis (2012) Goh et al. (2013) Nisar and Prabhakar (2018)
The weekly responses to customer reviews	The sum of the weekly number of responses from H Company to customer reviews in each post	Kumar et al. (2016)
The prizes value of weekly lucky draws	The value sum of the prizes of lucky draws provided by H Company each week	Li et al. (2007) Lee and Qiu (2009) Prendergast and Thompson (2010)
	User-generated content	
The weekly number of page views for each post	The sum of the number of page views for each post in a week	Bo and Shen (2015)
The weekly number of thumbs-up	The sum of the number of thumbs-up in each post issued in the same week	Li and Ku (2018)
The weekly proportion of positive comments	The average of each post's proportion of positive comments in a week	Chong et al. (2016) Schaer et al. (2019)

Table 2. Correlation between input-output variables

	Number of issued posts	Number of responses to customer reviews	Value of prizes in lucky draws
The weekly page views number for each post	0.3951** 0.0050	0.1821 0.2104	0.3334* 0.0193
The average proportion of positive comments	0.3340* 0.0190	0.5980** 0.0000	0.3099* 0.0302
The number of thumbs-up	0.4795** 0.0005	0.3030* 0.0343	0.1651 0.2569

Notes: * $p < 0.10$, ** $p < 0.05$, ***$p<0.01$

Table 3. Results of CE evaluation

Activity	Evaluated CE	Activity	Evaluated CE
1	0.69	26	0.905
2	0.761	27	0.946
3	0.683	28	0.848
4	0.555	29	1
5	0.742	30	0.765
6	0.727	31	1
7	0.835	32	0.868
8	1	33	0.836

9	0.571	34	0.571
10	0.645	35	0.805
11	0.746	36	0.91
12	0.907	37	0.582
13	0.853	38	0.836
14	0.752	39	0.848
15	0.611	40	0.906
16	0.86	41	0.767
17	0.583	42	0.934
18	0.605	43	0.941
19	0.773	44	0.602
20	0.786	45	0.946
21	0.931	46	0.764
22	0.627	47	0.714
23	0.617	48	0.948
24	0.787	49	0.616
25	0.917	Average value	0.784

Table 4. Estimated results of ARX-based time series analysis and coefficients

Variables	Definitions	Auto-regression analysis		ARX without CE		ARX with CE	
		Coefficient	T	Coefficient	T	Coefficient	T
$\ln D_{t-1}$	One order lagged online demand	0.417*	3.78	0.398*	3.56	0.389*	3.26
$Price_t$	Products' real transaction prices of Period t			-2.928***	-3.98	-2.605***	-3.58
$Springfestival_t$	Dummy variable for logistics outage in Spring Festival			-4.388***	-8.97	-4.148***	-10.42
$Season\ Factor_t$	Dummy variable represents different seasons			0.023	1.23	0.019	1.02
CE_t	CE Effect evaluated by DEA model of Period t					0.760**	3.25
Adjusted R^2		0.162		0.628		0.726	

DW Statistics	2.375	2.305	2.217
F Statistics	14.30	37.85	43.13

Notes: * *p < 0.10*, ** *p < 0.05*, ****p<0.01*

Table 5. Comparison of forecasting accuracy between different models

Forecasting Models	Root Mean Square Error （RMSE）	Average Absolute Error （MAE）	Mean Absolute Percentage Error （MAPE）
ARX with CE	1276	766	27.7%
ARX without CE	1577	808	39.9%
ARIMA	1863	1394	46.3%
Moving Average	1936	1936	60.2%