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Forecast Information Sharing for Managing Supply Chains in the Big Data Era: Recent Development and Future Research

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Sharing forecast information helps supply chain parties to better match demand and supply. The extant literature has shown that sharing forecast information improves supply chain performance. In the big data era, supply chain managers have the ability to deal with a massive amount of data by big data technologies and analytics. Big data technologies and analytics provide more accurate forecast information and give an opportunity to transform business models. In this paper, a comprehensive review on forecast information sharing for managing supply chain in the big data era is conducted. The value and obstacles of sharing forecast information are discussed. Given the sufficient data, the appropriate approaches of analyzing and sharing forecast information are highlighted. Insights on the current state of knowledge in each respective area are discussed and some associated pertinent challenges are explored. Inspired by various timely and important issues, future research directions are suggested.

Keywords: Forecasting; forecast information sharing; big data; supply chain.

1. Introduction

Due to the prevailing use of information technologies and social media networks, data collection is much easier and more convenient than that in the past. We are now in the big data era in which supply chain managers have the ability to access

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to a massive amount of data, namely, big data. Big data is a series of data that is extremely complex, very diverse, and in a heterogeneous form (Shi, 2014). Specifically, it is featured by high-volume, high-variety and high-velocity (McAfee and Brynjolfsson, 2012) that is hard to be managed and analyzed within a short period of time and its huge dataset is difficult to be processed using traditional applications (Jacobs, 2009; Chen and Zhang, 2014). Recently, researchers have widened the attributes of big data and included the characteristics of veracity (Gupta *et al.*, 2012; Buhl *et al.*, 2013; Zikopoulos *et al.*, 2013; Power, 2014) and value (Demchenko *et al.*, 2013) in their definition. Even though companies face various challenges when handling big data, they can gain more latest and deeper insights into consumer preferences and purchasing behavior when compared to what traditional analytics provided. By applying analytics, it helps to generate meaningful insights from the collected data through different techniques such as simulations, statistical analysis, and optimization (Wang *et al.*, 2015), and eventually, big data transforms business process, facilitates innovation, and improves firms' performance (Brown *et al.*, 2011). Retailers can gain at least 15% increase in return on investment by incorporating big data into business process (Fosso Wamba *et al.*, 2015). The business process can be improved with big data technologies and analytics by enhancing visibility of firm operations and performance measurement mechanisms (McAfee and Brynjolfsson, 2012). Big data along with the phenomenal growth in data collection, mining, and analysis for supply chain, industrialists and scholars have shown a growing interest to develop forecasting techniques in the big data era. Table 1 shows the definition of big data (in terms of 5 "V"s) and industrial examples of forecasting in supply chains in the big data era. The discussed industrial examples show that the big data is crucial to improve the forecasting quality in supply chains.

Supply chain is a complex system with full of uncertainty from both demand and supply sides. To reduce uncertainty, forecast information has played increasingly important role in supply chain management and influenced the supply chain performance. In the supply chain context, managers aim to coordinate the supply chain such that the entire supply chain performance is optimal and all supply chain members are better off (Panda, 2013). However, the willingness of sharing the forecast information of a supply chain member will significantly affect this achievement. For example, it is challenging to coordinate the supply chain if forecast information is private for an individual party or information sharing is partial and lacks of truthfulness. Therefore, the incentive scheme of forecast information sharing is crucial to the supply chain coordination (Wu *et al.*, 2012). The information sharing is critically important in the big data era as supply chain managers are increasingly reliant upon data to gain visibility in supply chains (Hazen *et al.*, 2014), but if data is not reliable, the inaccurate result of forecasting may even hurt supply chain performance (Oh and Özer, 2013).

A number of review articles on supply chains forecasting have been published over the last decade (e.g., Meade and Islam, 2006; Fildes *et al.*, 2008; Song and Li, 2008; Liu *et al.*, 2013; Eksoz *et al.*, 2014; Syntetos *et al.*, 2015). Recently, three

Table 1. Definition of big data and examples of forecasting in the big data era.

Attributes	Nature	Examples
Volume	Large volume of data	— Dell developes a database including *multiple million records* related with sales for better forecasting market demand (Davenport, 2006). — The department store Sears uses big data of *practices of millions of people*, to understand supply chain management, and better forecast online sales on the basis of a data set of product characteristics (McAfee and Brynjolfsson, 2012).
Variety	The large variety of sources and formats	— A steelmaker uses the *data from internal marketing and sales, as well as external suppliers*, to improve the accuracy of sales forecasts and make production more efficient (Dhawan *et al.*, 2014). — An automaker recently invests in *social media data* for improving production planning and forecasting (Court, 2015).
Velocity	Frequency of data generation/ delivery	— A global beverage company integrates *daily weather forecast data* from an outside partner into its demand and inventory-planning processes, which improved its forecasting accuracy by about 5% in a key European market (Brown *et al.*, 2011). — Retailers trace online individual customer's data from click stream, which can forecast their purchasing behavior (Manyika *et al.*, 2011)
Veracity	Consistency and trustworthiness of data	— eBay adopts the "virtual data mart" to mitigate the data duplication problem and develops a "data hub" to facilitate internal data sharing within the company (Davenport *et al.*, 2012).
Value	The added-value generated from the data	— An oil company conducts big data analytics to optimize production and minimize the downtime, eventually; it reduces operations and staffing cost by 10% to 25% but increases the production by 5% (Brown *et al.*, 2011).

review articles on the big data analytics in logistics and supply chain management aspects, as well as in the risk management domain have been conducted by Wang *et al.* (2015), Chan *et al.* (2016) and Choi *et al.* (2016), respectively. However, rare article discusses forecast information sharing with the consideration of big data. Big data is new and it has been a popular technique to enhance forecast accuracy in supply chains. According to the latest trends in the big data, it is important to review the articles of forecast information sharing and consider how the technologies and analytics of big data can be incorporated into forecasting. To the best of our knowledge, it is the first paper to review the literature of forecasting in supply chains in the era of big data. In this paper, we summarize the contributions of relevant literature and identify the challenges of improving forecasting accuracy in the presence of big data. Besides, we also address how to manage and analyze the collected data to make a better decision in the big data era.

The rest of the paper is organized as follows. Section 2 introduces the review methodology. Section 3 reviews forecast information and Sec. 4 presents the literature of forecast information sharing. Section 5 discusses forecasting models for supply chain in the big data era. Section 6 reveals the ways of sharing forecast information in the big data era. Section 7 concludes the paper and identifies areas for future research.

2. Review Methodology

This study is based on comprehensive reviews that require detailed article searching. We extensively searched Google Scholars, ScienceDirect.com, IEEE Xplore Digital Library, INFORMS Pubsonline, and EBSCO Business Source Complete database for the terms including "forecast", "supply chain", "big data", "demand prediction", appeared in the title or keywords. We focused on the archival operation management journals written in English. The searching was conducted from January 2016 to March 2016. The initial search identified 93 papers, and after screening of titles and abstracts, 62 of them are kept as they are related to the topic of forecast information sharing from 2000 to 2016.

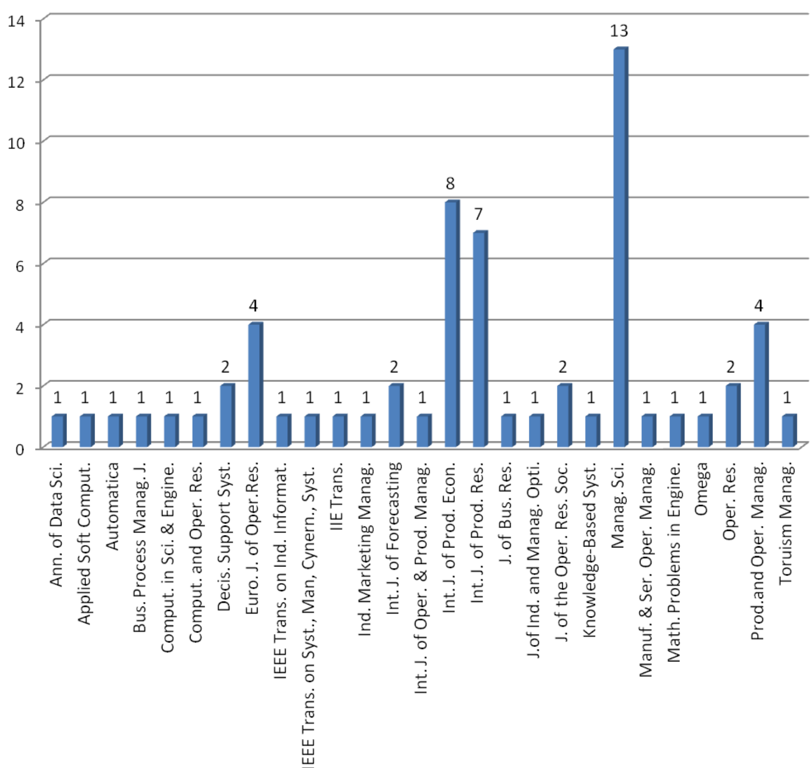

Fig. 1. Distribution of publications according to Journals.

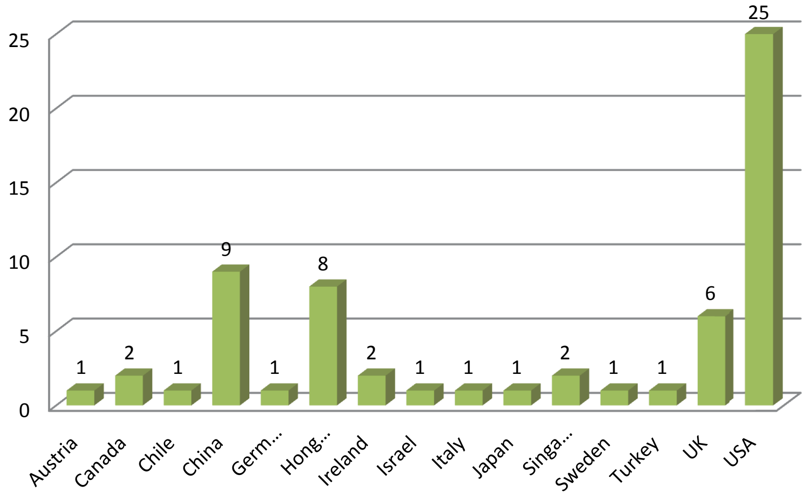

Fig. 2. Publications according to countries (first author's country).[a]

In Fig. 1, it shows that the journal *Management Science* has published 13 papers relevant to forecasting topics in supply chains, *International Journal of Production Economics* published 8 papers and *International Journal of Production Research* appeared 7 papers. Figure 2 demonstrates that scholars from USA are most interested in the topics of forecasting in supply chains with 25 published papers, and followed by China with 9 articles and Hong Kong SAR with 8 articles. Table 2 yields some interesting observation on the popularity of research approaches to examine the issues of forecasting in supply chains in terms of years from 2000 to 2016. We observe that (i) mathematical modeling is the most popular and common research approach to study supply chain forecasting, and (ii) in the recent years, scholars have paid more attentions on forecasting in supply chains.

3. Forecast Information

Forecast information plays a crucial role for managing supply chains and improving supply chain performance. Forecast information can be mainly classified into demand forecast information and supply forecast information. In particular, supply chain managers desire to improve their market demand forecasting accuracy in the big data era (Chase, 2013), and demand forecast information is greatly examined in the extant literature. Donohue (2000) examines demand forecast information and production decision in a two stage supply chain. They find that the degree of demand forecast improvement affect the efficient solution of price and supply chain performance. In supply chains, the bullwhip effects cannot be neglected as

[a]China represents the Chinese Mainland while Hong Kong represents Hong Kong SAR (China).

Table 2. Summary of research approaches in terms of years.

Research Approach	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Conceptual	1													1				2
Empirical study						1		1										2
Experiment												1						1
Mathematical modeling	2	2		1			4			3	3	4	2	3	1	5		30
Review							1		2					1	1	1	1	7
Simulation			2				1		1	1		1	2		1	1		10
Computational forecasting algorithms								1	2			1	3	1		2		10
Total	3	2	2	1	0	1	6	2	5	4	3	7	7	6	3	9	1	62

supply chain performance may be deteriorated when the bullwhip effects are serious. The causes of the bullwhip effect can be the demand forecast. Chen *et al.* (2000) study a two stage supply chain with demand forecasting and order lead times. They show the analytical evidence that the bullwhip effect can be reduced but not eliminated by the centralized demand information. Shin and Tunca (2010) investigate the incentive of investing in demand forecast with downstream competition in supply chains. They yield an interesting finding that when the retailers' forecast investments are not observable in the competing supply chains, an index price contract is able to fully coordinate the supply chain for profit optimization, whilst when forecast investments are observable to others in the competing supply chains, and then the forecast investments may increase. In the big data era, the data storage and collection are important parts of forecast investments. This is due to the fact that the approaches of data storage and collection may influence data quality, which further affect forecasting accuracy (Forslund and Jonsson, 2007). It is particularly true when firms invest in collecting massive data in retailing with three key demand information dimensions: locations, products, and time. An inappropriate data storage and collection may incur heavy forecast investment, which negatively affect supply chain performance (Hazen *et al.*, 2014).

Retailers estimated that using big data for demand forecasting has the potential to increase operating margin by more than 60% (Manyika *et al.*, 2011). Thus leading retailers pay huge attentions on demand forecasting. The advanced analytical models are proposed for demand forecasting in the retail industry. Kremer *et al.* (2011) analyze the forecasting behavior by using the controlled laboratory experiment based on time-series data. Their experimental results yield that subjects may overreact (under-react) to forecast error in the relatively stable (unstable) environment. Aburto and Weber (2007) develop a hybrid intelligent demand forecasting system with ARIMA models and neural networks for time series prediction. By using the real data from a Chilean supermarket, they find that their proposed system helps supermarket to quantify the effect of special events in sales, as a result, it facilitates a better inventory management. Ali *et al.* (2012) examine the effects of forecasting errors on inventory control by ARIMA models. They develop the forecasting model and assess the validity by using the real sales dataset from a major European superstore. In the big data era, in order to obtain more rich data in supermarket, Aburto and Weber (2007) argue that the new technologies such as EDI and RFID can provide rich basis for data mining applications in the retail industry. Bertolini *et al.* (2015) conduct a field study to show the importance of RFID adoption in fashion retailing. Vlachos (2014) highlights the value of RFID to improve stock availability and supply performance because RFID is considered to improve the management of supply chain processes as it can enhance demand forecasting (Vlachos, 2014).

Demand forecasting is important for new product development in high-tech electronics. In the big data era, the important task is to use big data to forecast consumers' unspoken needs (Li *et al.*, 2015). For example, Oliva and Waton (2009) examine the way of forecasting process to enhance the accuracy of forecast at a consumer electronics company. Their results reveal that the forecasting process is capable to manage the potential political conflict and the informational and procedural shortcomings. Ryu *et al.* (2009) compare the planned demand transferring method and forecasted demand distributing method in the high-tech electronics equipment supply chain. They further compare the difference of throughput, inventory level, and service level between the above two methods.

Consumer tastes evolve from time to time. As a result, forecast updating is particularly important for better managing supply chain. So and Zheng (2003) are motivated by the practices of demand forecast updating in the semiconductor industry. They develop a two-level supply chain model and examine the relationship of lead time and forecast updating on retailer's order quantity variability. Their analytical and numerical results show that the supplier's sufficient capacity is important to ensure the consistent delivery lead time during high demand season. Choi (2006) studies the quick response (QR) policy with dual forecast information updating in a two echelon fashion supply chain with single retailer and single supplier. He considers that the fashion retailer gathers the sale data of a pre-seasonal product in which its demand is closely related to the demand of the seasonal product, and applies this information to update the demand mean and demand variance of the seasonal product using the Bayesian approach. Under the situation with uncertain ordering and production costs, he derives the analytical conditions that QR policy is beneficial to the supply chain and proposes the measures to achieve Pareto improvement. Thomas *et al.* (2009) examine the effects of demand forecast updating in a supply chain consisted of an original equipment manufacturer (OEM) and a contract manufacturer (CM). They argue that the provision of forecast updating may be harmful to the OEM. They also computationally derive the conditions under which forecast updating and risk sharing are in the best interest of the OEM. Yang *et al.* (2011) consider that a fashion retailer can purchase the component from two different suppliers with different lead-times for product assembly. At the period after placing the first order from the long-lead-time supplier and before placing the second order from the short-lead-time supplier, retailer can update the demand forecast and hereafter may cancel the order partially from the long-lead-time supplier. Under this dynamic optimization problem, they find that forecast updating process does not affect the supply chain coordination mechanism. Choi (2013) proposes the supplier selection mechanism with the consideration of demand forecast updating and carbon emission tax issues in the fashion industry. The proposed supplier selection scheme consists of two-phase in which the first phase filters the inferior suppliers and second phase supports the optimal supplier selection from the non-inferior set by stochastic dynamic programming. Yang *et al.* (2015) evaluate the reservation pricing effects in a two stage fashion supply chain with forecast updating. They consider the case when the demand forecast is partially updated, under which they find that the supplier benefits from forecast update from the true information and higher capacity reservation. Zheng *et al.* (2015) investigate a two stage supply chain with a regular and an emergency order. By using dynamic programming, they find that the demand forecasting updating should be used for the quantities of both regular and emergency. The forecast updating accuracy is gradually improving with the big data applications. Indeed, the performance of the supply chain depends on the demand and supply conditions in real time basis (Choi *et al.*, 2016). The big data approach with the advanced technologies such as RFID in which the dataset can be updated rapidly can enhance the accuracy of forecast updating and the supply chain performance (Vlachos, 2014).

4. Forecast Information Sharing

Information sharing is one of the most critical objectives of processing the big data (Wu *et al.*, 2014) and is crucial in supply chain management. A large number of practitioners and scholars have shown the importance of information sharing in improving supply chain performance. It is observed that supply chain managers are more willing to share forecast information in supply chains. For example, large manufacturers tend to share forecast information with their buyers for forecasting accuracy improvement (Choi *et al.*, 2013). Sharing various types of forecast information from different sources enhances forecast accuracy and save supply chain partners' investment in forecasting. Moreover, forecast information sharing enhances transparency and reduces forecast errors in supply chains. The value of forecast information sharing is greatly investigated in the extant literature. Cachon and Lariviere (2001) study the value of demand forecast information sharing between forced and voluntary compliances. They yield an interesting result that the truthful forecast from the manufacturer can help to optimize supply chain performance, but the manufacturer has an incentive to inflate her forecast and induce supplier to prepare more capacity. Byrne and Heavey (2006) develop a model of business process re-engineering and examine how supply chain performance can be improved by enhancing information sharing and forecasting techniques. Their model quantifies the effects of collaboration for each party in supply chains. Yue and Liu (2006) study the value of sharing demand forecast information in a two stage dual channel supply chain. They consider the demand function as a linear function of price with a Gaussian primary demand (i.e., zero-price market potential), and supply chain parties set their price based on their forecast of the primary demand. They find that the demand forecast information significantly influences the price in the dual channel supply chain. Mishra *et al.* (2009) explore the value of demand forecast sharing from the retailer to the manufacturer. They demonstrate that the retailer may be hurt if he shares the demand forecast to the manufacturer unconditionally. They also show the significance of sharing demand forecast when considering social welfare and consumer surplus. Taylor and Xiao (2010) characterize the analytical results that the manufacturer tends to be hurt if the retailer's forecasting ability is enhanced under the scenario where the product economics are lucrative. Later, Barlas and Gunduz (2011) examine the impact of demand forecast information sharing on bullwhip effect in supply chains. Their results are consistent with the work by Chen *et al.* (2000), where bullwhip effect can be reduced but cannot be completely eliminated. In addition to bullwhip effect, competition effect is also significant for the value of forecast information sharing. Ha *et al.* (2011) study the incentive for information sharing under Cournot and Bertrand competition and derive the conditions that are beneficial to the supply chain. For instance, under the Cournot competition, information sharing benefits a supply chain when at least the retailer's information is less accurate, while under Bertrand retail competition, information sharing benefits a supply chain when information is more accurate. Zhu *et al.* (2011) examine a two stage supply chain where both the manufacturer and retailer forecast market demand independently. They consider different forecast information sharing cases and derive the conditions that the supply chain parties should share forecast information to achieve the best performance. Ali *et al.* (2012) compare the results of forecasting accuracy between the scenarios of forecast information sharing and no information sharing in a two stage supply chain. They find that the demand process affects the accuracy from forecast information sharing and the magnitude of the forecast accuracy improvement is related to inventory savings. In contrast to demand forecasting, supply forecasting is not widely examined in the extant literature. Trapero *et al.* (2001) assess the value of sharing sales information on the supplier forecasting accuracy by using weekly data from a manufacturer and a major UK grocery retailer. Based on the real data analysis, they argue that information sharing can improve supply forecasting accuracy.

Suppliers need to share various supply forecast information such as predicted raw material price and production capacity to retailers, whilst retailers need to share various demand forecast information such as predicted consumer perception and market conditions to suppliers. To guarantee the efficiency of information sharing, appropriate supply chain contracts are encouraged to be used between supply chain parties. Durango-Cohen and Yano (2006) study the equilibrium of forecast-commitment contract where the buyer provides forecast information, the supplier makes an order, and the minimum ordering quantity is a function of forecasting. They derive the dominant strategy for forecast commitment. In the era of big data, using the advanced information technologies such as enterprise resource planning (ERP), customer relationship management (CRM) may be included in the context of supply chain contracts.

However, to ensure the success of forecast information sharing, the big obstacle is the strong commitment of collaborative forecasting between supply chain parties, instead of the advanced information technology. Supply chain parties should address partners' mutual and long-term objectives for adopting collaborative forecasting (Eksoz *et al.*, 2014). Collaborative forecasting is widely examined in the extant literature. Helms *et al.* (2000) discuss the benefits of collaborative forecasting in a supply chain. They recommend that demand information should be supplied completely by supply chain partners for reducing forecast errors. Aviv (2001) compares supply chain performance of forecast information sharing with that of local forecasting, under which each member updates the forecasts of future demands periodically and forecast information are known locally only. He incorporates forecast information into replenishment processes and finds that the benefits of local forecast depend on the forecasting strengths, whilst the benefits of collaborative forecast are related to the diversification of forecasting capabilities. Kurtulus *et al.* (2012) explore the value of collaborative forecasting in retail supply chains via both non-coordinating and coordinating contracts. Their analytical results demonstrate that under non-coordinating contract, the collaborative forecasting helps to reduce the effect of double marginalization and the cost of supply-demand mismatch. Moreover, they argue that collaborative forecasting is valuable under the coordinating contracts. Advanced technology and techniques are prerequisites for forecast information sharing (Kerr and Tindale, 2011). Advanced technology and techniques include big data approach and analytics, which generate timely forecasts for short-life products such as fashion and food, and access to relevant, sufficient, and undistorted information within supply chains.

Supply chain parties may have concerns on the reliability and credibility in forecast information sharing. Özer and Wei (2006) examine the credible forecast information sharing and argue that the degree of forecast information asymmetry and the risk-adjusted profit margin are two important drivers that determine supply chain efficiency. Ren *et al.* (2010) study the practice of forecast sharing in supply chain coordination with a game-theoretical model. They characterize the equilibrium, where forecast information is transmitted truthfully and the supplier allocates the system-optimal capacity. They suggest the supplier should compute a scoring index of the customers' behavior if they have incentive to share private information. Özer *et al.* (2011) use the controlled laboratory experiments to examine when trust is important in forecast information sharing. Their experimental results reveal that the trustworthiness induces cheap-talk forecast sharing under the wholesale price contract. They argue the repeated interactions and information feedback influence trust and cooperation in forecast sharing. Gumus (2014) examines the credibility of forecast sharing in supply chains and indicates that the proper contract can ensure truthful forecast information. Specifically, he finds that the buyer can use request for quotation with quantity restrictions as a credible signal for forecast sharing. Shamir and Shin (2015) study the effects of information credibility in forecast information sharing and develop a model of an incumbent supply chain with the possible entry of a competing supply chain. They confirm the intuition that the retailer cannot credibly share the forecast information and that public information sharing can benefit all the firms in the market as well as consumers. Firouzi *et al.* (2015) investigate the importance of trust in supply forecasting in a supply chain. They consider the supplier can determine to share its forecast truthfully or not. They find that the supplier tends to deviate from sharing information when the forecast random yield shows that the supplier is reliable. Hence, in the era of big data, the reliability and credibility in forecast information sharing are crucially important in supply chains. The advanced information technologies can help to provide a transparent environment for supply chain parties to sharing forecast information.

Moreover, the big data approach and analytics can provide real-time forecast information to supply chain parties. The extant literature has discussed that real time information sharing without reservation may not be always beneficial to supply chain performance. It is important to get a clear picture of when is the best timing to share forecast information in supply chains. Oh and Özer (2013) study the role of time in forecast information sharing in a supply chain. Their results indicate that when the supplier postpones building capacity and screening the manufacturer's private information, the accuracy of forecast information is higher in the supply chain. Moreover, the postponement of building capacity may increase the degree of information asymmetry between the supplier and manufacturer, which further results a higher cost of screening. They also develop a framework to quantify the value of time for forecast sharing decision. Gao (2015) derives a Markov model with non-stationary volatile and dynamic nature of the forecast evolution and designs an easy-to-implement coordination contract. He argues that dynamic forecast is valuable for high margin product. Big data creates great business value from the real-time information sharing and decision making (Fosso Wamba *et al.*, 2015). If data has sufficient quality by the time, an accurate correlation could help the organization to conduct a correct analysis of business opportunities and make a better decision (White, 2012).

The market demands are greatly dynamic especially in the high-tech industry. The downstream supplier should receive more accurate demand forecast information from upstream retailer for better positioning inventory level and production planning. Thus forecast sharing is significantly important in the high-tech supply chain. Terwiesch *et al.* (2015) empirically examine the forecast sharing process in supply chains based on a large amount of data in the semiconductor industry. According to the results from a duration analysis, they find that the suppliers penalize buyers for unreliable forecast by providing lower service levels and the buyers penalize suppliers by providing overly inflated forecasts. They argue that a supply chain may not be able to achieve the potential performance improvement from forecast sharing. Yan and Wang (2012) study the value of information sharing in a high-tech franchising supply chain by the Bayesian forecasting method. Their results yield an interesting finding that high-tech franchising firms can benefit from information sharing of demand forecasts and the profit sharing contract can achieve centralized profit optimization in a franchising supply chain.

Forecast information sharing involves many important topics such as value of sharing, trustworthiness of sharing, collaborative forecasting, and timing of sharing. Table 3 summarizes the literature of forecast information sharing.

Table 3. Summary of the reviewed literature on the forecast information sharing.

Authors	Industry	Method	Approach	Key problems problems	Value sharing	Trustworthiness of sharing	Collaborative forecasting	Timing of sharing
Aviv (2001)	Functional products	Mathematical model	Game theory	Collaborative forecasting, CPFR, coordination			✓	
Barlas and Gunduz (2011)	N.S.[2]	Simulation	(s, S) policy	Demand forecast, lead time	✓			
Byrne and Heavey (2006)	Industrial SME	Case study	Discrete event simulation	Information sharing, forecast techniques	✓			
Cachon and Lariviere (2001)	N.S.	Mathematical model	Game theory	Demand forecast, Asymmetric Information, coordination	✓			
Donohue (2000)	Fashion	Mathematical model	Game theory	Demand forecast, forecasting update, lead time, coordination	✓			
Durango-Cohen and Yano (2006)	Capital-intensive manufacturing industry	Mathematical model	Game theory	Supply strategy, forecast dominant commitment strategy, information sharing			✓	
Firouzi *et al.* (2015)	N.S.	Mathematical model	Game theory	Supply forecast		✓		
Forslund Jonsson (2007)	N.S.	Empirical study	Survey based	Forecast information sharing, forecast information quality		✓		
Gao (2015)	N.S.	Mathematical model	Dynamic programming	Collaborative forecasting, coordination, dynamic forecasting				✓
Gumus (2014)	N.S.	Mathematical model	Game theory	Price competition, request for quotation		✓		
Ha *et al.* (2011)	N.S	Mathematical model	Game theory	Supply chain competition, Demand information sharing	✓			

[2]N.S. represents not specified.

Table 3. (*Continued*)

Authors	Industry	Method	Approach	Key problems problems	Value sharing	Trustworthiness of sharing	Collaborative forecasting	Timing of sharing
Helms *et al.* (2000)	N.S.	Conceptual	—	Collaborative forecasting			✓	
Kurtulus *et al.* (2012)	Retail industry	Mathematical model	Game theory	Collaborative forecasting, information sharing			✓	
Mishra *et al.* (2009)	N.S.	Mathematical model	Game theory	Demand forecast	✓			
oh and Ozer (2013)	N.S.	Mathematical model	Game theory	Demand forecasts, asymmetric forecasts				✓
Ozer and Wei (2006)	N.S.	Mathematical model	Game theory	Coordination		✓		
Özer *et al.* (2011)	N.S.	Mathematical model	Behavioral experiments	Asymmetric forecast information		✓		
Ren *et al.* (2010)	N.S.	Mathematical model	Game theory	Demand forecast sharing, Truthfulness		✓		
Shamir and Shin (2015)	N.S.	Mathematical model	Game theory	Truthfulness, supply chain competition		✓		
Taylor and Xiao (2010)	N.S.	Mathematical model	Game theory	Information asymmetry, supply chain contract	✓			
Terwiesch *et al.* (2005)	Semiconductor industry	Empirical study	Secondary data analysis	Demand forecast, unreliable forecasts		✓		
Trapero *et al.* (2012)	Supermarket	Simulation	—	Demand forecast, supplier forecast sharing	✓			
Yan and Wang (2012)	High-tech industry	Mathematical model	Game theory	Information sharing, information asymmetry	✓			
Yue and Liu (2006)	N.S.	Mathematical model	Game theory	Demand forecast, pricing	✓			
Zhu *et al.* (2011)	N.S. N.S	Mathematical model	Game theory	Demand forecast sharing	✓			

5. Forecasting Models for Supply Chain in the Big Data Era

In the big data era, firms collect data from operational data warehouses, cloud computing data centers, shared information on social network websites, and intelligent sensor networks. Given sufficient data, it is important to develop forecasting models for data mining and analytics for gaining the accurate and useful forecasting information. This forecasting information can be further shared between supply chain parties. In this section, three kinds of forecasting models are summarized and discussed with the concept of big data analytics.

5.1. *Novel applications of advanced forecasting models for managing supply chains with big data*

Scholars have developed many advanced forecasting models with big data application for managing supply chain. Due to the high variety feature of the big data, various forecasting methodologies and robust procedures are needed to deal with massive data (Wang *et al.*, 2015). Hybrid forecasting methods have been drawn a great attention as they are constructed by combining the strengths of different forecasting methods (Liu *et al.*, 2013). For example, Aburto and Weber (2007) develop a hybrid intelligent demand forecast system with autoregressive integrated moving average (ARIMA) models and neural networks. By using the proposed replenishment system, they show improvements from proposed demand forecast system in terms of sales failures and inventory level compared with the previous solutions. Au *et al.* (2008) develop an optimal evolutionary neural network (ENN) for demand forecasting in which it uses the evolutionary computation approach to search the network structure. By analyzing the two years real sales data of two apparel products, it is found that the proposed algorithms is more accurate than that of the fully connected neuron network for time series demand forecasting, and is also superior to the traditional seasonal autoregressive integrated moving average (SARIMA) model for the products characterized by low demand variation and weak seasonal trends. Choi *et al.* (2011) propose a seasonal autoregressive integrated moving average (SARIMA) wavelet transform (SW) sales forecasting method for fashion products. By deploying both real industrial data and artificial data, they find that the SW method performs better than the traditional statistical forecasting method and it is appropriate to apply for the products with volatile demand. Xia *et al.* (2012) study a forecasting model that incorporates both extreme learning machine model and adaptive metrics to improve the forecasting accuracy when the available data is sufficient. The adaptive metrics of inputs can resolve problems of amplitude change and trend determination, and lower the effect of network's over-fitting. Giloni *et al.* (2014) study the value of forecast information sharing in a multi-stage supply chain where the retailer faces ARIMA demand. The research approach helps managers to better manage supply chain by sharing forecast information. Babai *et al.* (2013) use ARIMA approach to examine the value of forecast information sharing. They analyze the data from 320 stock keeping units in a major European supermarket and prove that forecast information sharing is beneficial to forecasting error reduction and inventory planning. Ren *et al.* (2015) propose the panel data-based particle-filter model to forecast market demand in the fashion industry with limited data. They use the real sales data from the fashion industry and the simulation results reveal that the proposed panel data model outperforms both traditional statistical and intelligent methods. They find that the proposed panel data model has a better forecasting accuracy in item based than that in color based. Moreover, their analysis shows that the larger amount of historical data does not necessarily improve forecasting accuracy. This proposed approach is important in the fashion industry as they find that it is not necessary to have a large amount data for demand forecasting. Recently, Arunraj and Ahrens (2015) develop two forecasting models; i.e., hybrid SARIMA using multiple linear regression (SARIMA-MLR) model, and SARIMA and quantile regression (SARIMA-QR) model, in which they consider the external demand influencing factors (such as promotion effect and weather effect) for conducting sales forecasting in food supply chain management. By applying the models for forecasting the sale of banana from a retail store, they find that both models have a higher forecasting accuracy when compared with the traditional SARIMA and multi-layered perceptron neural network (MLPNN) models. In particular, the SARIMA-QR model generates better estimating intervals and provides more insights on the effect of external demand influencing factors for different quantiles than that of the SARIMA-MLR model.

5.2. *Simulation analysis of advanced forecasting systems and supply chain management*

Many advanced forecasting systems adopt the simulation approach for supply chain management analysis. Zhao *et al.* (2002) study a forecasting model selection process for sharing information in a supply chain. They use computer simulation model to examine demand forecasting and inventory replenishment decisions by the retailer, as well as production decisions by the suppliers. Their results reveal that information sharing can reduce the cost substantially and the proper forecasting models can help to improve supply chain performance. Zhao *et al.* (2002) examine the impact of forecasting errors on supply chain performance by simulation. They surprisingly find that a slight positive bias in the retailer's forecast can actually increase the benefit of sharing information for the supplier and the entire supply chain. Their findings motivate the companies to share information in which it can reduce the forecasting errors.

In the big data era, simulation analysis is one of the most significant approaches for forecasting market demand and supply. Besides, it results in a more favorable environment to conduct simulation analysis when there are significant amounts of data available (Belaud *et al.*, 2014). In the existing literature, Byrne and Heavey (2006) conduct a discrete event simulation and investigate lead time and inventory behavior with or without information sharing. The simulation results are obtained through the real industrial case study that about 10% supply chain cost is saved after adopting information sharing and forecasting techniques. Huang *et al.* (2008) develop a real option approach based on demand forecasting. The real option approach effectively pictures the long-term trends and random variation involved in a given demand stochastic diffusion process. They conduct a Monte Carlo simulation to solve the demand forecasting model and use demand forecasting model to determine the provisioned smoothing capacity during the upcoming planning horizon. Ho and Ireland (2012) examine the effects of forecasting errors by conducting a simulation test in an ERP-controlled manufacturing system. The simulation results imply that the proper lot-sizing rules are recommended to copy with forecast errors. Prestwich *et al.* (2014) propose several mean-based error measures and evaluate forecasts against the mean of the underlying stochastic process by simulation. They claim that the proposed measures can be used to compare forecasters on intermittent demand.

Because of the massive data availability under the big data era, a recent study investigates the effect of big data toward the forecast accuracy. Hofmann (2015) conducts a simulation experiment by employing both control theory and system dynamics approach to show how big data reduces the forecasting errors and bullwhip effects in supply chains. He finds that the big data variety enhances customer sentiment-based forecast accuracy. In addition, he also observes that the big data feature of velocity (i.e., the capability of combining different sources of data) is a critical element which can enhance the supply chain efficiency.

5.3. *Big data driven forecasting models and decision making in supply chains*

With the development of information technology, big data driven forecasting model have been greatly adopted in supply chains. The leading retailers are responsible for monitoring the in-store movements of customers as well as examining how to interact with the products such that they can predict consumer behavior more accurately (Brown *et al.*, 2011). Carbonneau *et al.* (2008) use the advanced machine learning techniques including neural networks, recurrent neural networks, and support vector machines to forecast market demand in a supply chain. By comparing the performance in term of error, they find that the recurrent neural networks and support vector machines perform the best, but their forecasting accuracy is not statistically significantly better than that of the regression model. They conclude that using the advanced machine learning techniques for forecasting demand provide more accurate information in supply chains. Beutel and Minner (2012) introduce two data-driven frameworks for demand forecasting and safety stock determination with the assumption that market demand is dependent of the external factors such as price and weather. In the first framework, Beutel and Minner employ the regression models to conduct forecasting and show how to plan the safety stock level according to the forecast errors. On the other hand, in the second framework, they use the linear programming with the consideration of different objectives and service level constraints to estimate the target inventory function. Simmhan *et al.* (2013) develop a cloud-based software platform to conduct big data demand analytics. This platform is able to integrate the real-time data and dynamic data sources, and facilitate information sharing between different parties securely. In addition, they adopt the scalable machining-learning models to train the massive data for demand forecasting and deploy the social medial tools (e.g., Web portal and mobile apps) to identify the energy consumption pattern.

6. The Ways of Sharing Forecast Information in the Big Data Era

The information and communication technologies (ICT) are supported by the big data technologies and analytics, and greatly implemented for forecasting collaboration (Fan *et al.*, 2015). The advanced ICT should be carefully evaluated before implementation as they add complexities into decision making process (Barlas and Gunduz, 2011). This is particularly true in the big data era. Data mining techniques are complex to be incorporated into supply chain system for forecast information sharing within supply chain parties. To better investigate the big data application in supply chain systems for forecast information sharing, we discuss three major strategies that can motivate channel members to facilitate forecast information sharing in supply chains in the following sub-sections.

6.1. *Vendor-managed inventory (VMI)*

VMI partnership is widely adopted in many industries. Disney and Towill (2003) find that the adoption of VMI can offer a significant opportunity to reduce the bullwhip effect in real-world supply chains because it encourages information sharing. To effectively facilitate VMI partnership in supply chains, forecast information sharing is necessary. In particular, the implementation of VMI requires the supply chain parties to adopt collaborative forecasting Holweg *et al.* (2005). VMI partnership provides technical supports for the downstream supply chain parties to replenish periodically via an automatic ordering program (Kiesmüller and Broekmeulen, 2010). For example, in fashion industry, TAL launches the VMI strategic partnership with JC Penney. By accessing the JC Penney's point-of-sale (POS) data, TAL can conduct the demand forecasting for JC Penney and better plan its own production schedule (Chow *et al.*, 2010). The automatic ordering program of VMI is ideally supported by the big data technologies and analytics.

6.2. *Collaborative planning, forecasting and replenishment (CPFR)*

CPFR is a technique that combines intelligence of all supply chain partners to plan and fulfill the customer request. The well-known example of CPFR is Wal-Mart and its suppliers such as Procter & Gamble and Johnson and Johnson (Li and

Zhang, 2015). CPFR provides an excellent platform for managing supply chains with forecast information sharing. It receives great attentions from industry after the advanced information technologies are greatly invented. In the big data age, CPFR is widely adopted by many retailing companies. Under CPFR, supply chain parties share forecast information and co-manage the important business processes in supply chains. To successfully implement CPFR, it not only requires the commitment of both business and technical resources, but also a high degree of collaboration to share forecast information. Big data technologies and analytics can incorporate into CPFR system, where the common demand forecasting for supply chain partners are generated (Fan *et al.*, 2015).

6.3. *Quick response (QR)*

QR relies on the supply chain partners' help in offering vital data to assist quick and sound decision making (Choi and Sethi, 2010). QR is considered as an efficient consumer response strategy under the volatile demand markets through reducing the order lead time (Hammond, 1990), and this strategy is substantially benefited by the big data technologies and analytics. QR is widely adopted in the retail firms such as Zara, where suppliers and buyer (i.e. Zara) share forecast information via the advanced information systems. The QR supply chain addresses short response time, which implies that the supply chain parties should be encouraged to share information, such that it can improve the demand forecast, mitigate the bullwhip effect and facilitate better production planning and scheduling in the supply chain system.

7. Conclusion and Future Research

Big data approach and analytics provide more accurate forecast information and changes the business models. Sharing forecast information is significantly important in supply chains, particularly in the big data era. In this paper, we conduct a comprehensive review and discuss various important issues in forecast information sharing in the big data era. The types of forecast information in supply chains are identified and discussed. The approaches and benefits of forecast information sharing are highlighted and discussed. Moreover, we present several forecasting models and address important strategies that can induce forecast information sharing in the big data era. In this following, we propose the future research directions.

7.1. *Sustainability issues*

Over the past few years, we have seen the establishment of new sustainability tool and measurement in supply chains. Firms are looking for efficiency but ignore sustainability. Sustainability includes social, economic, and environmental challenges. We argue that forecast information sharing can help to better match supply and demand, namely, reduce waste in supply chains. The well-known example is the collaboration between Wal-Mart and P&G, where a joint development of forecasts and replenishment plans reduce waste by enhancing forecast information sharing. It is interesting and important to examine the issues including (i) the impacts of forecast information sharing on enhancing sustainability, (ii) what kind of information (e.g., full information, partial information, fake information) affect firms' sustainability response, and (iii) how big data approach and analytics can be incorporated into supply forecast information collection for enhancing sustainability. These issues are all timely and important for future exploration.

7.2. *Information dimensions for forecast information sharing in the big data era*

Supply chain information includes many dimensions such as echelon, location, product, and time (Syntetos *et al.*, 2015). All these information dimensions are closely related to the important issues such as production planning and inventory management. As a result, all these information dimensions are essential for conducting supply chain forecast. In the future research, it is interesting and important to investigate (i) the impacts of the single dimension on forecast information sharing, and (ii) how the big data technologies and analytics affect the information dimensions in terms of forecasting. These problems are promising as well as challenging for future research.

7.3. *Supply forecast information*

Supply information and demand information are equally important in supply chain management. However, according to the extant literature, there is a lack of intensive research on the supply forecast information in supply chain management. This is mainly because of the difficulties of examining supply forecast information with the current information technology. This situation may change after the big data technology and analytics are well-developed. In the future research, it is important to examine (i) how supply information data is collected for further analysis, (ii) what dimensions are important for supply forecast information, (iii) after data collection, what approaches and analytics can be used for improving the accuracy of supply forecast and hence the supply chain performance, and (iv) which incentive scheme can help to share the supply forecast information efficiently. These issues are all timely and important for future investigation.

7.4. *Forecast information in reverse logistics*

In the existing literature, it is found that most of the studies focus on the demand forecasting issue in the forward supply chain. On the other hand, product return that is related to the reverse supply chain is also well-observed in real world practice; however, this issue is under-explored. Besides, information technology such as RFID system can enable real time data collection and is a crucial tool in the big data era. Therefore, it is interesting to explore the following topics: (i) how to incorporate the return issue in the study for demand forecasting in the big data era, and (ii) what is the value of using RFID technology for demand forecasting with the consideration of product return.

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