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Perspectives on supply chain forecasting

1. Introduction

Supply chain forecasting as a descriptor aims to capture all aspects of forecasting to support operations, from the retailer or service provider through the distribution system to the manufacturers and third tier suppliers.[1] Aspects of this problem area figured prominently in the early literature on forecasting, with R.G. Brown's books connecting forecasting with inventory management being pivotal (Brown, 1959, 1963). Brown's innovations led to the development and implementation in software of exponential smoothing, still the workhorse of many companies' forecasting systems 60 years later. In the founding of the two forecasting journals, forecasting to support supply chain operations was identified as part of the scope, and Brown himself contributed to the first issue of the *Journal of Forecasting* (Brown, 1982).

However, the topic has largely been neglected since the early contributions, with relatively few articles being identified as influential by Fildes (2006). Instead, the focus has been at the level of the individual stock keeping unit (SKU) series, with less attention being paid to the aggregate level. Of course, some statistical methods such as Box-Jenkins and, more recently, the state space formulation of Hyndman, Koehler, Ord, and Snyder (2008) have proved influential in the forecasting methods implemented in supply chain companies: through commercial software for ARIMA methods and through open-source software in the state space case. Likewise, the various Makridakis competitions (most recently the M4 competition; see Makridakis, Spiliotis, & Assimakopoulos, 2018), which have compared various univariate methods of forecasting over different forecasting horizons using various loss functions, have influenced the methods used in practice, though this influence has been indirect, acting through the methods and choice algorithms included in commercial software. However, methodologically, the bulk of the research published in the forecasting journals has used novel econometrics with applications in the macroeconomy.

In practice, supply chain forecasting is ubiquitous, with every company that is involved in responding to customer demand employing staff with the oversight of forecasts. While their job titles may vary from demand planner to sales forecaster or analyst, a major part of their job is to provide forecasts of demand to other parts of the company, especially operations, production, distribution, and finance. The neglect of the challenges faced by supply chain forecasters might suggest that the early methods of Brown, Holt, Box and Jenkins have continued to provide successful technical solutions to the problems undoubtedly experienced by these organizationally-based forecasters, since, if correct, there would be little need for improvements. However, a review of the literature does not support such a conclusion. Forecasting-related research in a supply chain context is published in a wide variety of journals, just not in the two journals dedicated to forecasting! This neglect in the forecasting journals has had unfortunate knock-on consequences, in that much of the research that has been published elsewhere has not kept up with the methodological issues that have been aired, in particular, in the specialist forecasting journals.

In recognizing this omission, the editors of this Special Issue have had two aims in mind: to publish high quality research with a direct focus on supply chain forecasting, and to re-focus the research community on the various important outstanding research issues, including the implications of 'big data' for supply chain forecasting. It has also been our intent to illustrate standards of good practice in this important research area, as, all too often, methods are proposed in other research communities that are not validated by any evidence. Remember Goodwin's law: "If the name of a method [or parameters in the model] contains more words than the number of observations that were used to test it" then be sceptical (Goodwin, 2011, 2017).

This brief introduction does not attempt to contribute a full literature review of supply chain forecasting; there have been a number of recent surveys which we cite in the relevant sections. However, a full literature search was undertaken in a wide variety of journals using key words including 'supply chain', 'operations' and of course 'forecast', and the key journals in the area turned out to be

[1] 'Supply chain consists of all the parties involved directly or indirectly, in fulfilling a customer demand' (Chopra & Meindl, 2013), a definition expanded on by Syntetos, Babai, Boylan, Kolassa, and Nikolopoulos (2016).

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the *European Journal of Operational Research*, *International Journal of Production Economics*, *International Journal of Production Research*, *Management Science*, and *Manufacturing and Services Operations Management.* The list of contributors obtained through this search was used as the basis for inviting contributors, both to a workshop held in Lancaster in June 2016 and to contribute to this special issue. In addition, the special issue, together with a related topic of 'big data', were advertised in the *IJF*. The results embraced the wide range of topics that falls under this umbrella heading. Section 2 introduces the key 'actors' and activities in supply chain forecasting. The various research areas which have developed, often somewhat separately, are discussed in Section 3, together with the limitations in scope and methodology that arise in each topic. We conclude with suggestions as to where the major opportunities are to be found, both for research and in practice.

2. The activity of supply chain forecasting

Fig. 1 depicts the information that flows through the supply chain to form the basis for each tier's forecasts, as well as some of the drivers that affect sales and orders.

In addition to the information flows shown in Fig. 1, the manufacturers and their suppliers may also be provided with forecasts (of orders or sales) by their downstream partners. These many sources of information must then be integrated into a 'final forecast', in effect the operating forecast shared across the organization. This will usually be done through a Sales and Operations Planning Process (S&OP) and ERP technology. The process may be simpler in a service operation, but the core elements of a forecasting support system and judgmental interventions remain the same. Neither the functioning of S&OP (Seifert, Siemsen, Hadida, & Eisingerich, 2015; Thomé, Scavarda, Fernandez, & Scavarda, 2012; Tuomikangas & Kaipia, 2014) nor the role of technology have attracted much research attention (Asimakopoulos & Dix, 2013).

However, the S&OP process, and demand management more generally, has been successful in gaining considerable practitioner attention (see for example Chase, 2016). The terminology here is one of demand sensing and demand shaping, terms that mean little more than developing demand models which include downstream higher frequency (EPOS) data, marketing plans and promotions, and the product mix (Chase, 2016). Once such models have been developed, the company can attempt to optimize costs and revenues to achieve a more profitable position. However, the reality of implementation is much more difficult than this description implies. While revenue management in airlines and hotels is now common practice, adoption in retailing has been more limited (but see Natter, Reutterer, Mild, & Taudes, 2007, for an example in a DIY chain), though the models do exist (e.g. Ma & Fildes, 2017).

So, if more advanced methods of demand sensing have not yet been adopted widely, what are current forecasting practices in the supply chain? Weller and Crone (2012) provide the most recent survey information. As in the previous surveys of forecasting practice, they find that simple methods are used most commonly, often with exponential smoothing at their heart. Judgmental adjustments to the statistical forecasts are commonplace, with the aim of taking into account the complexities faced by the forecasters. The one area in which there has been much modelling activity is where the demand data are intermittent. For more than 20 years after the original article by Croston (1972), little if any research attention was paid to the topic, despite its practical importance. Since then, though, there has been a blossoming of new methods dealing with the problem of intermittent demand, with corresponding changes in software, to such an extent that a book focussed on the topic is needed.

As Fig. 1 illustrates, expanding the information used for modelling demand for all tiers in the supply chain offers prospective value as a means of mitigating forecast error. This growth in both the volume and type of customer transaction data through EPOS and the click-stream data associated with sales both on-line and through brick-and-mortar stores, has the potential to stimulate new methods and models, which indeed are beginning to appear in the literature (see e.g., Boone, Ganeshan, Jain, & Sanders, 2019).

The focus of most forecasting research has been on point forecasts, evaluated through a standard forecasting accuracy metric (such as the mean absolute percentage error). The linkage of forecasting to the organization's supply chain offers the potential for expansion of the forecasting model class to be considered, emphasizing not only the point forecast but also the corresponding predictive uncertainty. A key issue for supply chain operations has long been how the effects of demand uncertainty and forecast errors can be contained. The standard approach in practice (and in much theoretical work as well) has been to ignore the uncertainty, beyond using safety stocks to protect service levels. Standard inventory control theory, as reproduced in textbooks, has often recommended an inappropriate formula that does not address forecast uncertainty adequately, while forecasting theory has been decoupled from inventory control models. At the disaggregate (SKU) level, models are needed that specifically link demand distribution parameters to forecasting methods that properly take into account the forecast uncertainty. At the aggregate (organisational) level, once forecasting is embedded in a supply chain context, service level/investment trade-off curves are needed (see for example Gardner, 1990).

In summary, the issues that we editors see as important to the development of supply chain forecasting are:

- The processes and systems through which the disaggregated forecasts are produced
- Methods and selection algorithms that are suitable for supply chain data
- The impact of new data sources from both the consumer and supply chain partners
- The effects of uncertainty and forecast errors on the supply chain

and, most importantly,

- The effects of linking forecasting to supply chain decisions, at both the aggregate and disaggregate levels.

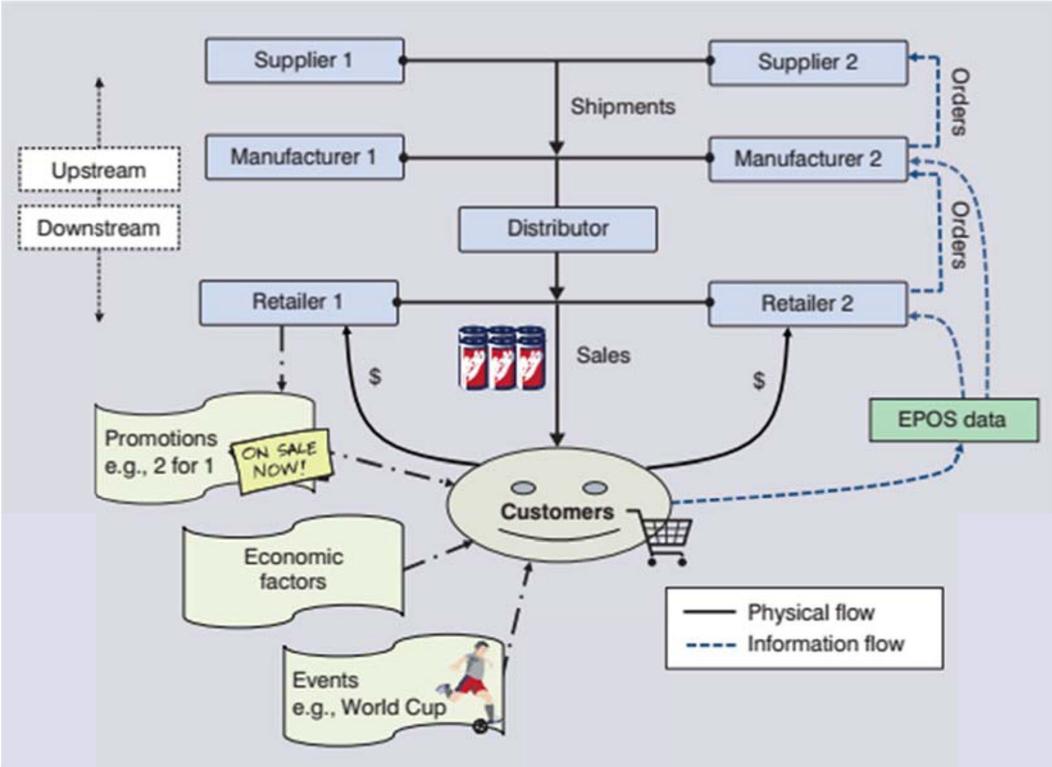

Fig. 1. Information flows and exogenous drivers.
Source: Taken from Ord, Fildes, and Kourentzes (2017).

3. Current issues

3.1. The processes and systems of supply chain forecasting

The process by which supply chain forecasts are produced and negotiated, leading to a 'final forecast' that is adopted by other functions in the organization, is complex. Research on the way in which organizations go about the process is limited (but see for example Goodwin, Lee, Fildes, Nikolopoulos, & Lawrence, 2007; Moon, Mentzer, & Smith, 2003). In contrast, practitioner-oriented articles, books and seminars are common (see the literature review by Syntetos et al., 2016). Three approaches to understanding more about the interactions of the many actors and the resulting effects on forecast accuracy and organizational performance are available.

(i) The first is through organizational case studies, of which there are few. Kaipia, Holmström, Småros, and Rajala (2017) and Oliva and Watson (2009, 2011) examine how organizational disincentives and functional power can be damaging and how these negative factors can be moderated. A key question for those who are working to develop better technological solutions is why many organizations make the apparently irrational decision to ignore superior forecasting methods and remain committed to their inefficient processes (Brown, 2011). In this issue, Phillips and Nikolopoulos (2019) show how an action research approach using various model-based tools to support their interventions can succeed in stimulating an organization to adopt radically new practices, not only in the area of forecasting, but also in its production planning.

(ii) Experimental studies have become common, although most are abstracted from the key features that forecasters face in an organisational setting. Many studies are concerned directly with the way in which forecasters respond to time series, e.g., their autocorrelation structure, their volatility or their trend (see Harvey & Reimers, 2013, for a recent example). However, within the supply chain, the adjustment of some baseline statistical forecast is more common, where the forecaster responds to various pieces of information including a baseline forecast. In a supply chain setting, some studies, such as that by Kremer, Siemsen, and Thomas (2016), have identified a theoretically interesting problem (in their study, hierarchical forecasting) in an attempt to understand how judgmental forecasts respond to the probabilistic interactions in the hierarchy. In this issue, Fildes, Goodwin, and Onkal (2019) focus more on capturing elements of the organizational interactions where information is shared, in order to understand how such information affects the final operational forecast. The results suggest that information will often be seriously misinterpreted in such a realistic setting, with implications for the design not only of the organizational processes, but also of the forecasting support system.

(iii) Field studies always capture some of the key features of the organizational interactions in the supply chain, including the use of a forecasting support system where there are typically many series being forecast. Early examples that focused on forecasting were the various papers by Blattberg and Hoch (1990) and Mathews and Diamantopoulos (1986). However, the recent works by Fildes, Goodwin, Lawrence, and Nikolopoulos (2009) and Franses (2014) have stimulated new interest in understanding how business forecasters respond to the various pieces of information they collect. The research has typically focussed on behavioural hypotheses such as the likely benefits of combining models with managerial intuition, with Blattberg and Hoch even suggesting an ideal ratio of 50–50 on average. The strength of field studies is that they can confirm (or undermine) the results of experimental studies and suggest more complex conditional hypotheses.

Despite the growth of research in this area of behavioural forecasting, our editorial opinion is that there is still too little emphasis on organizational practices with their biases and inefficiencies, and what could be done to improve performance.

3.2. Novel forecasting methods and selection algorithms

Automatic forecasting methods that can cater for large numbers of products are a key feature of supply chain forecasting, with the workhorse still being exponential smoothing. Software packages now typically include a variety of standard methods including regression with trend (and seasonality), moving averages, and ARIMA. A selection algorithm must then be used to select between these methods, and also within a family of methods (such as exponential smoothing). Software companies such as SAP and SAS, as well as many more specialised providers, have developed procedures that automate the selection between methods or their combination. Evidence has accumulated showing that standard implementations of selection, for example when based on the within-sample fit, are inadequate and can lead to substantial unnecessary losses (Fildes & Petropoulos, 2015). On this issue, Villegas and Pedregal (2019) have taken the state space characterisation of time series and, using an automatic selection routine, demonstrated its uniformly strong performance relative to well-established competitors: the comparison made is for 166 products sold in food franchises with daily forecasts being made 1–14 days ahead, a practical operational problem. Anecdotal evidence suggests that organizations all too often use poorly implemented algorithms, and rarely consider new and better alternatives, despite the benefits.

3.3. Capitalizing on supply chain data characteristics

Supply chain data have some characteristics which can be taken advantage of in order to produce better forecasts. From a market planning perspective, decisions are based on cross-sectional product hierarchies from SKUx Store to SKU to Brand to Category. Research has established both optimal methods for aggregation (see e.g. Athanasopoulos, Ahmed, & Hyndman, 2009) and the benefits of pooling across a cross-section to identify seasonal effects (Boylan, Chen, Mohammadipour, & Syntetos, 2014) or marketing mix decisions (Gür Ali, Sayin, van Woensel, & Fransoo, 2009). From an inventory management perspective, purchase decisions are dictated by supplier lead-times. This leads very naturally to the examination of temporal aggregation for demand forecasting, particularly if the unit of aggregation is taken to be the lead-time itself. More sophisticated approaches to temporal aggregation allow several levels of aggregation to be taken into account simultaneously, allowing higher frequency and lower frequency features to be forecast at the most appropriate levels (Kourentzes, Petropoulos, & Trapero, 2014; Nikolopoulos, Syntetos, Boylan, Petropoulos, & Assimakopoulos, 2011; Spithourakis, Petropoulos, Nikolopoulos, & Assimakopoulos, 2012).

Intermittent demand is common across many supply chains, and calls for forecasting methods that are appropriate for this type of data. There has been some progress over the last fifteen years, with various new forecasting methods having been introduced to support decision-making in relation to stock replenishment and to the withdrawal of an item from stock. There have also been some advances in determining the choice of forecasting methods (Babai, Syntetos, & Teunter, 2014; Syntetos, Boylan, & Croston, 2005), as well as rather slower progress in the development of a satisfactory modelling framework for intermittent demand, which would allow for the analytical construction of prediction intervals and the automatic selection of forecasting methods. In some application areas, for example in aerospace, it is also possible to make use of maintenance data to improve demand forecasts. However, this important question has not received the attention it deserves, although interest has been growing in recent years. It is therefore timely that the current issue provides a review and critique of the literature on this topic (van der Auweraer, Boute, & Syntetos, 2019).

3.4. Big data

Over the past ten years, a profusion of data has become available to forecasters and planners. Technologies are now able to track customer clickstreams and browsing patterns, both in-store and online, which gives insights into consumer behaviour; social media and Internet searches provide new variables that can enhance forecast models; and embedded devices ("Internet of Things") are enabling track-and-trace in the supply chain, with the potential to improve the efficiency of supply chain operations. These datasets bring with them the promise of *personalization* to the customer of products, services, promotions, and price; *improved* product forecasts, and better *managed* supply chain *risk* (see (Boone et al., 2019), who explore advances in customer analytics as they relate to supply chain forecasting).

Much of the research on big data forecasting has focused on adding search traffic or social media variables (like Twitter, YouTube and Facebook) to traditional time series models (see Boone et al. (2019), and Schaer, Kourentzes, and Fildes (2019), for reviews of these models). Examples of the successful use of such internet variables include the prediction of economic indices, stock market sentiments, the spread of disease, and traffic studies in tourism and entertainment. While most of these studies seem to indicate that such internet and/or social media variables reduce forecast errors, there is some debate as to (a) which variables to include; and (b) whether these models can be used for supply chain forecasting. Yu, Zhao, Tang, and Yang (2019) provide an example of one way of identifying appropriate (internet) search terms for predicting oil consumption, and then go on to show that these terms do improve prediction. On the other hand, using evidence from two case studies, Schaer et al. (2019) suggest that many of the models that use these internet variables have not been evaluated rigorously, and question the benefits that can accrue from these new variables. As was discussed earlier in this editorial, one important advantage of doing such research in the forecasting community is the adherence to established principles of forecasting and rigorous evaluation.

It is our editorial opinion that the forecasting community thus far has taken a rather myopic view of big data. We suggest that the research agenda should be expanded, from simply augmenting traditional time series models with new variables, to cover three areas (see also the essays in Singhal, Feng, Ganeshan, Sanders, & Shanthikumar, 2018, Special Issue of the *Production and Operations Management* journal on "Perspectives on Big Data"). First, there is a significant potential in the "mining" of customer browsing and buying behaviour: this can potentially be used for real time personalization, promotions and campaigns, and the identification of patterns and trends in rapidly changing markets. However, the increasingly stringent protection of personal data, particularly in the EU, may limit the use of such data. As was noted above, there has been only limited research on the gains in forecast accuracy that can be achieved by "mining" this data. Second, embedded devices are increasing transparency in the supply chain, by helping in coordinating with supply chain partners, monitoring and utilizing assets, and managing risk in the supply chain. The premise here is that significant operational gains can be obtained by making supply chain processes (and failures) more "predictable". This is a promising area for empirical research. Finally, we see an emerging research area in securing the privacy and security of data and in ensuring that the algorithms that mine data are free of bias and discrimination. Many of the methods that are used for data security are based on "outlier" detection; and bias and discrimination can be reduced by "scoring" the algorithms – both of which areas the forecasting community is ideally suited to studying.

3.5. Forecast uncertainty and forecast error, and their impacts on supply chain performances

In inventory management, there has long been a disconnection between forecasting and the choice of optimal inventory models. Many inventory models are based on deterministic demand. At best, inventory models allow for a stochastic error term, which is usually stationary with independent errors and a known demand distribution, but with no consideration of the errors in estimating demand parameters. The optimality that these papers purportedly demonstrate is spurious, with results that may support much simpler models. For example, Fildes and Kingsman (2011) show that it is important to distinguish between demand uncertainty and forecast accuracy in a manufacturing/inventory planning context, with the result that the standard EOQ formulation for ordering dominates so-called optimal models. In this issue, Prak and Teunter address estimation uncertainty in inventory models. They compare a traditional approach with an approach that takes into account estimation error, and show that the latter method can result in significant cost-benefit improvements. Also in this issue, Trapero, Cardós, and Kourentzes point to the potential pitfalls of assuming that forecast errors have a zero mean and constant variance. They discuss a number of alternative approaches that avoid this assumption and result in robust performances.

There has been considerable debate over the last thirty years over the most appropriate forecast error measures. One of the catalysts for this debate was the original M-competition (Makridakis et al., 1982). This debate led to an emphasis on scale-independent measures, in order to overcome the problem of a small number of series dominating an error metric. However, these early discussions were based on context-free error measures, with no consideration of the impact of the errors on supply chain decisions and performance. The importance of this issue became clear when considering intermittent demand forecasting. If more than 50% of periods have zero observations, then, according to the mean absolute error measure, the optimal forecast is zero – but this is hardly optimal from a supply-chain perspective, unless a decision has been made not to stock the item at all! One suggestion is to use suitable loss functions for evaluating alternative forecasting methods, showing the importance of choosing an appropriate method that recognizes the supply chain planning process and goes beyond standard statistical measures. Petropoulos, Wang, and Disney (2019) examine the relationship between accuracy measures and inventory performance. Unlike in the case of intermittent demand, standard accuracy measures such as MAPE do reflect the service-inventory trade off for their data set, and they find that the temporal aggregation method of combining forecasts is the best performer overall. Bias (rather than accuracy) has often proved particularly important in determining system performance, and in Petropoulos et al.'s study, the methods with the lowest biases are often the least accurate. We conclude that methods should be evaluated on the type of data for which they are designed, with an evaluation framework that matches the application (for example, for call centre planning, with methods that include multiple seasonality).

4. A research agenda

Despite the long history of forecasting and its application in supply chain planning, many fundamental issues remain unresolved. Here, we have highlighted intermittency, data aggregation and uncertainty. The progress in influencing the central direction of supply-chain research has been slow, with too many papers still making standard and inappropriate or invalid assumptions. We cannot emphasize too strongly that research which assumes that demand is either known or constant with known parameters is close to useless: at the very least, sensitivity tests must be carried out with data that mimic the reality of observed demand data or the stochastic nature of the demand built into the models.

New prospects are developing from the expansion of supply chain data, and these perhaps offer the most immediate rewards. External vertical collaboration has long been seen as offering a route to major improvements, but evidence of large-scale success is limited. This is still a rich research area with the potential to help upstream suppliers in the chain. For the retailer, though, internal data from customers' search and purchasing behaviours seems to us more likely to add substantial value. This may be enhanced further by multivariate algorithms that capture the simultaneity of customer activity, although, as Schaer et al. (2019) demonstrate, the incorporation of user-based content is far from easy. How much in-store (and website-based) behaviours can be harnessed to improve forecasts and profitability remains a more open question. While the technology is operational (e.g. RFID, in-store CCTV), the first problem is to establish robust relationships to the demand. However, customer response to the new marketing and promotional innovations that must be developed based on these relationships is perhaps more problematic. Equally problematic is the demands placed on the supply chain, where within-day changes in the forecast, and therefore the ordering, require potentially difficult system and process changes.

The role of artificial intelligence and machine learning methods in supply chain forecasting remains underexplored: the benefits and pitfalls of AI are not understood well in this context. Forecasting researchers should be active in gaining an understanding of what deep learning approaches can bring to supply chain forecasting, including what advantages they can bring compared to statistical models and shallow neural networks.

The role of forecasting support systems in determining the effectiveness of the forecasting activity, as we mentioned, is under-researched. The current spate of research on the behaviours of supply chain forecasters and judgmental adjustments linked to ordering behaviour is to be welcomed. However, if improvements are to be made, the conclusion that such forecasts are often inefficient with consistent biases is not particularly helpful. First, more needs to be discovered about the organizational processes of supply chain planners. While accuracy has been established as the most important objective for demand planners, other KPIs are likely to affect the overall performance. Second, the ways in which the current software is used, the data embodied in it, the screen cues that demand planners face and the effects of S&OP-like interactions need study. After that, we can start to research the key question of how the demand planners' job and the support systems they rely on can be reconfigured to make gains. The improvements in performance will only come from processes, algorithms and systems – the audit by Moon et al. (2003) shows the need to enhance all these components – but the financial and environmental benefits of better supply chain forecasting remain substantial and worth the research effort.

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