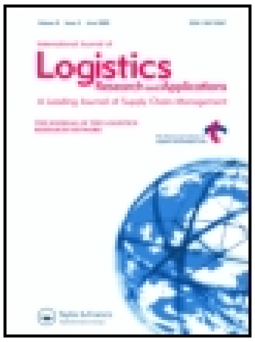

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Impact of big data on supply chain management

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ABSTRACT

This study focuses on big data, which offer new opportunities, added value and operational excellence for existing supply chain practices. A survey was conducted among employees of multinational companies across the United States, the Middle East, Europe, Asia and Australia. Structural equation modelling was employed for the statistical analysis of the survey data. The results show that demand management, vendor rating, the Internet of things (IoT), analytics and data science affect the supply chain industry regarding operational excellence, cost savings, customer satisfaction, visibility and reducing the communication gap between demand management and supply chain management (SCM). The adoption of big data technology can create considerable value-added and monetary gain for firms and will soon become a standard throughout the industry. This research provides a new description of the Supply Chain Operations Reference (SCOR) model by incorporating big data and SCM.

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KEYWORDS
Big data; supply chain management; demand management; vendor rating; analytics; data science; Internet of things

1. Introduction

Analytics is the process of developing actionable insights through problem definition and the application of statistical models and analysis against existing and simulated future data (Cooper 2012). It entails translating large volumes of information and complex data into precise, clear and meaningful information through advanced statistical analysis to enable users to make more accurate and fact-based decisions (Davenport and Harris 2007; Chen et al. 2011). Data analysis is revolutionizing the business spectrum, enabling improved business processes and organisational performance, thus giving businesses a competitive edge (Sharma and Bhat 2014). Recent technological advancements in the collection and storage of data and advanced tools of analysis, especially for unstructured data, have overwhelmingly transformed the nature of work and the working environment. Analytics is needed in today's business environment to understand trends and draw meaningful inferences from big data, intending to improve business performance. The supply chain industry gathers enormous amounts of data using radio-frequency identification (RFID), sensory information, tracking devices, etc. (Zhong et al. 2015). Exploiting these data with the help of information technology (IT), i.e. business intelligence insights, analytics and so on (Wamba et al. 2015), could help improve existing supply chain practices, reduce costs and provide better inventory management (Christopher and Ryals 2014), resulting, in turn, in increasing profits in the supply chain industry. Furthermore, as discussed, big data analytics can be of considerable use across the supply chain, including procurement, manufacturing, distribution and marketing (Sanders 2016). Also, dynamic decisions along the

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supply chain have traditionally demanded sophisticated information-sharing processes (Wood, Reiners, and Srivastava 2017).

The term 'big data' describes the large volume of structured and unstructured data which is growing exponentially and is analysed using analytics and data warehousing. The term was defined by Gartner as a '4V' framework, consisting of high volume, high velocity, high veracity and high variety information, which uses various processing measures to ensure better decision making (Sipahi and Timor 2010) through the use of analytics (Greco and Aiss 2015) to improve processes and ensure business optimisation (Hilbert 2016). The adoption and use of innovative IT and digital tools act as a critical resource for supply chain optimisation and this transformation has changed the definition of competition within the marketplace, i.e. rather than 'firm versus firm', it is now 'supply chain versus supply chain' (Ketchen and Hult 2007).

Supply chain management (SCM) gathers tremendous amounts of data from various processes, i.e. the use of sensors, RFID and tracking devices, serving as a breeding ground for the generation of big data. The concept of big data helps to improve visibility by providing an integrated framework for monitoring performance and customer interaction through real-time data analysis and critical decision-making scenarios, thus mitigating risk and supply chain disruption and failures (Blanchard 2014). The ubiquity of mobile computing and the volume of data generated have opened up new frontiers for improving processes, as well as new gateways for measuring demand, understanding problems better and planning for the future (Toole et al. 2015).

A review of the literature shows that many studies have been conducted on the impact of data analysis and the use of various data-processing methods with the objective of extracting meaningful information from the data generated by the supply chain industry to increase profits (Handfield, Sroufe, and Walton 2005), enhance operational efficiency (Klindokmai et al. 2014) and gain competitive advantage (Klein, Rai, and Straub 2007). Thus big data are used to develop forecasting techniques (Li and Wang 2015), facilitate logistics (Thomas and Griffin 1996), develop better pricing mechanisms (Sipahi and Timor 2010) and assure customer satisfaction, repeat custom and vendor management (Alftan et al. 2015), as well as to facilitate risk assessment (Fawcett et al. 2011). The main focus of this paper is to explore less researched factors, such as demand management (Christopher and Ryals 2014), vendor rating (Muralidharan, Anantharaman, and Deshmukh 2001), the Internet of things (IoT) (Ng et al. 2015), analytics (Chae 2015) and data science (Waller and Fawcett 2013) in relation to SCM, along with the factors already addressed in the literature, to develop a model which focuses on the impact of big data in the supply chain industry.

Although much work has been done, still there are few gaps between big data theory and supply chain practices and many questions still remain unanswered, e.g. how to leverage big data volumes and unstructured supply chain data (Mortenson, Doherty, and Robinson 2015). It has been argued that exposure to digital data will result in an increase in spending on gadgets, telecom services and big data security and management tools (McCafferty 2014). In addition, very limited research has been done on the impacts of big data on customer satisfaction (Das 2012), operational efficiency (Metzger et al. 2015), better pricing and cost savings (Chase 2015) and real-time data analytics (Bardaki, Kourouthanassis, and Pramatari 2012) in the supply chain industry. This research is designed to derive insights into these measures to aid those using big data and thereby add substantial value to the supply chain industry.

2. Literature review and research framework

There is an existing body of literature that has inspected the impact of big data on SCM concerning various factors – data science, IoT, analytics, demand management and vendor rating – as summarised and discussed in Table 1.

Table 1. Comparative outcomes from previous studies for the variables used in this research.

Author/s	Findings	Scope for further research
1. Waller and Fawcett (2013) Finding	**Analytics** Using quantitative and qualitative methods to improve supply chain design and competitive power by analysing past data and by integrating business processes, functions, costs and service levels with the help of big data analytics in SCM. **Data Science** Advanced analytics is likely to become a decisive competitive asset in many industries and a core element in companies' efforts to improve performance using data science principles.	**Analytics** Managers need to understand and embrace the role of data science, predictive analytics and big data (DPB) and the implications for supply chain decision making. **Data Science** DPB will transform the ways in which supply chains are designed and managed, presenting a new and significant challenge to logistics and SCM.
2. Kwon, Lee, and Shin (2014)	**Analytics** Use of big data analytics to strengthen market competition and to open up new business opportunities, internal or external sourcing of data, data quality management and data usage experience solutions.	**Analytics** Hesitance of firms in adopting big data.
3. Christopher and Ryals (2014)	**Analytics** Analytics solutions developed with a view to reducing obsolescence of goods and wastage. **Demand Management** Emergence of demand management (along with new manufacturing techniques and big data), enabling supply chains to run concurrently with lower inventory costs and fast customer responses. Demand management uses both lean and agile methodologies.	
4. Zhong et al. (2015)	**Demand Management** Implementing big data approach in decision making, i.e. logistics planning and scheduling, with data collected using RFID on manufacturing shop floors. Mix of supply chain quality management and technology to improve SCM. **Data Science** Use of RFID cuboids to establish data warehouses, mapping with other cuboids and using spatio-temporal sequential logistics trajectories to perform logistics operations.	**Analytics** Use of more sophisticated systems with improved technologies to improve quality. Lack of information management in supply chain.
5. Da Xu, He, and Li (2014)	**Internet of Things** Building powerful industrial systems and applications exploiting the ubiquity of RFID, wireless and mobile technology and sensors using IoT.	**Internet of Things** Implementation of major IoT applications in the industry.
6. Ng et al. (2015)	**Internet of Things** Impact on SCM of the development of IoT or Internet-connected objects (ICOs) to meet customer needs by incorporating personal ICO data into various customisable applications (a 'platform strategy') and by maximising consumer value.	**Vendor Rating** Providers need to put mechanisms in place to enable customised solutions to emerge and place their strategic focus on their platform and the design of standardised interfaces. **Demand Management** Slow transition from product to platform focus, which requires a shift in supply chain logic from linear to network, web or eco-system thinking.
7. Chae (2015)	**Vendor Rating** Using social media (e.g. Twitter, Facebook, news services, etc.) for data sharing, hiring professionals, communicating with shareholders, identifying customer sentiments, enhancing sales performance, meeting environmental standards and identifying risks and associated disruption in the supply chain to select the best vendors.	**Analytics** Delay in analysing social media data (big data analysis) for research practices in SCM. **Vendor Rating** Developing insights into the potential role of Twitter in SCM (i.e. professional networking, stakeholder engagement, demand management, product development, risk management).

Note: All the variables influencing this research on SCM were identified from the scope for future research identified in the above articles from ISI Thomson Reuter journals.

2.1. Demand management

As noted in Table 1, a big data approach to decision making for logistics planning and scheduling using data collected via the use of RFID or sensors on manufacturing shop floors can be employed to assess customer demand and needs in real time (Zhong et al. 2015). Moreover, demand management (along with new manufacturing techniques and big data) can enable the supply chain to run concurrently, ensuring lower inventory costs and fast customer response times. Demand management also deals with the obsolescence of goods and wastage, especially for perishable goods, for which both agile and lean methodologies may be used (Christopher and Ryals 2014). To understand customers, global positioning system (GPS)-based surveys impose a lower respondent burden, offer greater accuracy and precision and incur fewer monetary costs, ultimately helping to understand demand and related issues better (Shankar 2015). GPS is a satellite-based navigation system, often adapted for surveying, as it can give a position (latitude, longitude and height) directly, without the need to measure angles and distances between intermediate points.

2.1.1. Bullwhip effect

The bullwhip effect refers to the gap that is caused by an increase in demand and a decrease in the volatility of inventories (Sourirajan, Ramachandran, and An 2008). The compelling study of the trade-off between responsiveness to demand and volatility can reduce the bullwhip effect. The bullwhip effect affects the SCM process through variations in a customer's demand pattern and this result is amplified progressing through the production, supply and distribution processes. Examples include fluctuations in lead times due to transportation (delivery times) and the distortion of replenishment/manufacturing orders generated by each member of a traditional supply chain. The impact of that distortion on the fill rate, inventory costs and transportation costs can be illustrated using a dynamic simulation model for the management of demand in multilevel supply chains (Bolarín, Frutos, and McDonnell 2009). Using agile methodology in high demand scenarios can prove beneficial for a firm's SCM (Lin and Lin 2006).

2.1.2. Total quality management and logistics

The three fundamental stages of supply chain procurement, production and distribution are undergoing transformation to keep up with market globalisation and competitive pressure, as well as to ensure a quick response to customer needs. Competitive pressure forces firms to reduce costs and improve customer service with the help of IT and logistics options. Proper coordination between the various stages of a supply chain ensures a near-perfect supply chain model (Thomas and Griffin 1996). Accurately forecasting customer demand is a crucial part of providing a high-quality service, ultimately also leading to a positive impact on vendor rating. Goldman, Nagel, and Preiss (1995) noted that the customer's needs should be included in the development of product, process and service, further emphasising the role of total quality management practices in relation to customer satisfaction.

2.1.3. Build-to-order supply chains

A build-to-order supply chain strategy helps improve the competitiveness of an organisation by meeting the demands of individual customers through leveraging the benefits of outsourcing and IT. IT is one of the essential factors in enhancing operations and facilitating the implementation of build-to-order supply chains (Gunasekaran and Ngai 2005). Howells (2014) has mentioned that the future of supply chains is not that there will be only chains or no chains at all, but that they will transform into demand networks. As a result, we posit the following:

> H1: Demand management is positively moderated by the impact of big data, leading to efficient supply chain management.

2.2. Vendor rating

Vendor rating is another determining factor in the supply chain industry. Social media, such as Twitter, Facebook, news services, etc., can be used for sharing data, hiring professionals, communicating with stakeholders, measuring customers' sentiments concerning companies' delivery services and sales performance and analysing environmental parameters to mitigate risks and disruptions. Moreover, the use of social media enables firms to rate various vendors on these factors (Chae 2015).

2.2.1. Analytic hierarchy process

The analytic hierarchy process (AHP) helps decision makers determine the varying degrees of importance of the flow of inputs and provides a strategic perspective in rating suppliers. Supplier selection helps firms meet requirements concerning quality, delivery schedules and the price offered (Muralidharan, Anantharaman, and Deshmukh 2002). However, the AHP may be biased and thus the application of statistical tools is used to estimate the confidence level in continuously evaluating vendors (Muralidharan, Anantharaman, and Deshmukh 2001). For example, Honeywell selects its vendors based on a confidence level of 90% or above.

2.2.2. Qualitative and quantitative analysis of vendors

It is crucial to procure the right quality of material in the right quantity from the right source. Vendors should be selected based on meeting quality requirements, delivery performance and the price offered, not only to meet immediate demand but also to cater to future demand. An interpretive structural model can be used to show the interrelationships between different criteria and their level of importance in the vendor selection process. Moreover, certain qualitative aspects, such as 'willingness to work', 'attitude' and 'after-sales service', may be evaluated to form the basis for vendor selection (Mandal and Deshmukh 1994).

2.2.3. Vendor selection systems

Vendor selection systems can be divided into various categories based on the time frame (short term vs. long term) and content (logistic vs. strategic). Vendor selection systems use the AHP framework to segment customer and supplier relationships concerning time and the nature of integration between the supplier and customer and by defining the selection criteria to be included in the vendor selection system. Integrating all these selection criteria in the vendor selection system helps determine ratings for vendors (Masella and Rangone 2000). Thus, we hypothesise as follows:

> H2: Vendor rating is positively moderated by the impact of big data, leading to better supplier–customer relationships and thus efficient supply chain management.

2.3. Big data analytics

The application of big data analytics in SCM has been referred to as SCM data science (Waller and Fawcett, 2013), which includes the application of advanced quantitative and qualitative analysis to a vast volume of structured and unstructured data. Such analyses include predictive analytics (Schoenherr and Speier-Pero 2015), business analytics, big data analytics and supply chain analytics (Wang et al. 2016). Predictive analytics, in particular, is a major factor in SCM in forecasting business trends and anticipated demand, minimising stock-outs, even during periods of unanticipated demand, as in recent years. It can be used to understand the hidden potential of SCM concerning the skills required (Schoenherr and Speier-Pero 2015). Big data analytics can be used to strengthen market competitiveness and improve data quality management and the data usage experience. A positive relationship has also been shown between maintaining the quality of big data and the perceptions of firms towards adopting big data analytics via internal or external sourcing of data (Kwon, Lee, and Shin 2014). In spite of the many benefits of the application of big data in supply chains, there are certain barriers to implementing predictive analytics, such as the lack of skilled professionals, lack of awareness and a dearth of tools for training the next generation of data scientists in the supply chain industry (Schoenherr and Speier-Pero 2015).

2.3.1. Predictive analytics and forecasting

Predictive analytics of sales data can be used to predict and forecast future demand for goods (Chase 2015). Predictive analytics is also used to examine customer purchase behaviour and provide purchase suggestions (Greco and Aiss 2015). The use of sensory networks to predict the remaining life of perishable goods is also possible with the help of predictive analytics (Li and Wang 2015). Thus, we suggest the following:

> H3: Data analytics and insights into customer demand patterns have a significant impact on managing demand in supply chain management.

2.3.2. Tracking of goods

Tracking tools that use sensory and tracing data provide support for supply chain decision making concerning logistics and SCM. Sensory data-driven supply chains exhibit better pricing models and better performance (Li and Wang 2015). According to Gartner (2014), to enhance in-transit visibility, IoT will 'significantly alter how the supply chain operates' and specifically the impact will relate to 'how supply chain leaders access information'.

2.3.3 Vendor-managed inventory and centralised planning and forecasting

Lack of collaborative practices among vendors causes challenges in inventory management, especially for perishable goods. Centralised forecasting and planning based on retailers' sales data can be used to forecast the entire supply chain and ensure better responsiveness to demand through the improved availability of products (Alftan et al. 2015).

2.3.4. Use of analytics to improve accuracy

Problem forecasting can be used to address potential problems proactively before they occur through predictive monitoring techniques, such as machine learning and constraint satisfaction using quality of service agreements. Predictive monitoring can help reduce lead times by 70%. Precision and accuracy can be improved up to 14% using constraint satisfaction through quality of service agreements. Moreover, the recall rate can be improved by 23% using machine learning and constraint satisfaction (Metzger et al. 2015). Therefore, we posit the following:

> H4: Data analytics powered with big data has a significant impact on customer satisfaction in SCM.

2.4. Data science

Data science, predictive analytics and big data, known collectively as DPB, play a vital role in decision making. DPB also ensures competitiveness by assessing the past and future integration of the business processes, cost levels and service levels of companies (Waller and Fawcett 2013). Advanced analytics is likely to become a decisive competitive asset in many industries and is a core element in a company's efforts to improve performance using data science principles (Waller and Fawcett 2013). The use of RFID cuboids to establish data warehouses, mapping with other cuboids and using spatio-temporal sequential logistics trajectories to perform logistics operations are examples of the application of data sciences in the supply chain industry (Zhong et al. 2015).

2.4.1. Collaborative partnership to reduce risks

Corporate logistics is used to share information with the aim of enabling the integration of disparate information amongst supply chain partners. The sharing of strategic information and customisable information technology ensure performance gains and symmetry of participation (Klein, Rai, and

Straub 2007). Investments in IT make the greatest contribution to competitiveness in enabling dynamic supply chain capabilities (Fawcett et al. 2011). Therefore, we propose:

> H5: Data science acumen in vendor processes has a significant impact on vendor selection and rating in supply chain management.

2.4.2. Lack of trust and competitive pressure

The importance of information in a downstream supply chain is considerable as inputs are proffered to those immediately upstream. Steps to minimise data distortion by competitors are of the utmost importance to prevent sales or order variance. Distrust among suppliers or vendors can have a negative impact on the four sources of the bullwhip effect, i.e. demand signal processing, the rationing game, order batching and price variations. Steps should be taken to ensure the accurate flow of information concerning delivery plans, production scheduling and inventory control (Lee, Padmanabhan, and Whang 2004). Therefore, we propose:

> H6: Data science has a significant impact on SCM by enhancing operational excellence for stakeholders with the use of big data technology.

2.5. The Internet of things

IoT has a significant impact on the supply chain industry due to the increasing number of Internet-connected objects (ICOs). With ICOs, customers' needs for personalised products are met through tailor-made solutions with profitability and customer value in mind (Ng et al. 2015). In building a powerful industrial system, applications can be integrated using IoT based on the ubiquity of RFID, wireless and mobile technology and the availability of sensory data (Da Xu, He, and Li 2014). Technology such as RFID and cloud-based or GPS systems play a pivotal role in in-transit visibility. These are the backbones of IoT as they are related to the supply chain (Shankar 2015).

2.5.1. Automation using radio-frequency identification

RFID uses radio waves to mark an object using a unique identification number embedded in a silicon chip. RFID tags are of two types: active (sensory network-based) and passive (providing the identification number and information for tagged objects wirelessly) (Borriello 2005). The affordability of RFID tags ensures their use in low-cost goods and the standardisation of technology enables uniform operations across RFID components. RFID enhances promotional management and exploits the dynamic pricing of goods by facilitating improved product visibility (Bardaki, Kourouthanassis, and Pramatari 2012).

2.5.2. Lack of regulation

With the advent of Internet-based technical architecture and integration with SCM, there is a considerable threat to data privacy and security. The adoption of legislation and development of architecture is required to prevent infringement of client privacy and ensure controlled access. The use of RFID in a controlled and safe way should be practised (Weber 2010). Therefore, we posit:

> H7: the Internet of things makes a significant contribution in providing real-time data visibility in supply chain management through big data analysis.

Table 2 provides a summary of the constructs and indicators, based on the review of the aforementioned literature.

3. Research methodology

The research was conducted using both primary and secondary data. The secondary data were collected through a literature review of 79 articles in ISI Thomson Reuters, leading to the identification

Table 2. Summary of proposed indicators and constructs based on literature review (scope of future research).

Item No #	Indicator	Based on Reference	Constructs
Q1	Bullwhip Effect	Sourirajan, Ramachandran, and An (2008); Bolarín, Frutos, and McDonnell (2009); Lin and Lin (2006); Meixell and Wu (2007)	**Demand Management**
Q2	Total quality management and Logistics	Thomas and Griffin (1996)	
Q3	Build to order supply chain	Gunasekaran and Ngai (2005)	
Q4	Analytical hierarchy process	Muralidharan, Anantharaman, and Deshmukh (2002); Muralidharan, Anantharaman, and Deshmukh (2001)	**Vendor Rating**
Q5	Inadequate investment	Klassen and Vachon (2003); Vachon (2007)	
Q6	Voting Analytics/Multi Criteria Decision Making	Liu and Hai (2005); Hadi-Vencheh and Niazi-Motlagh (2011)	
Q7	Qualitative and Quantitative analysis of vendors	Mandal and Deshmukh (1994)	
Q8	Vendor selection system	Masella and Rangone (2000)	
Q9	Confidence level analysis	Muralidharan, Anantharaman, and Deshmukh (2001)	
Q10	Automation using RFID	Bardaki, Kourouthanassis, and Pramatari (2012)	**Internet of things**
Q12	Lack of IOT regulations	Weber (2010)	
Q13	Sentiment analysis of customers	Das (2012)	
Q14	Predictive analytics	Chase (2015)	**Analytics**
Q15	Forecasting	Li and Wang (2015)	
Q16	Tracking of goods during disruptive scenarios	Li and Wang (2015)	
Q17	Vendor Managed Inventory	Alftan et al. (2015)	
Q18	Centralised forecasting and planning on vendor sales data	Alftan et al. (2015)	
Q19	Use of analytics to improve accuracy	Metzger et al. (2015).	
Q20	Collaborative Partnership to reduce risk	Fawcett et al. (2011)	**Data Science**
Q21	Lack of trust and competitive pressure	Lee, Padmanabhan, and Whang (2004)	
Q22	Analytical Hierarchy Process for better pricing and demand management	Sipahi and Timor (2010)	

of the independent variables argued to affect big data in SCM. The five independent variables are demand management, vendor rating, analytics, IoT and data science. These independent variables are the factors affecting the role of big data in SCM. To examine this, a detailed questionnaire was used and surveyed. The relationship between the effect of the five independent variables and big data on SCM is depicted in Figure 1.

3.1. Data collection

An email invitation was sent out to SCM professionals to complete the online survey questionnaire which was used in the collection of primary data. The questionnaire was developed using questions the validity and reliability of which have been solidly evidenced in papers in high-impact journals. Pre-testing of the questionnaire was done with a sample of 63 industry participants, all of whom had techno-functional expertise in SCM and in-depth knowledge of big data and its applications across industries, such as manufacturing, trading and services. Feedback from participants and personal interviews with some of the experts, namely chief executive officers (CEOs) and chief information officers (CIOs) of leading organisations in Singapore, were used to improve the questionnaire. The final questionnaire contained five measures for the five independent variables and three to five questions to measure each of the dependent variables, as well as three questions concerning the demographic profiles of the survey participants. A five-point Likert scale was used to measure the indicators (anchored at 1 = strongly disagree and 5 = strongly agree).

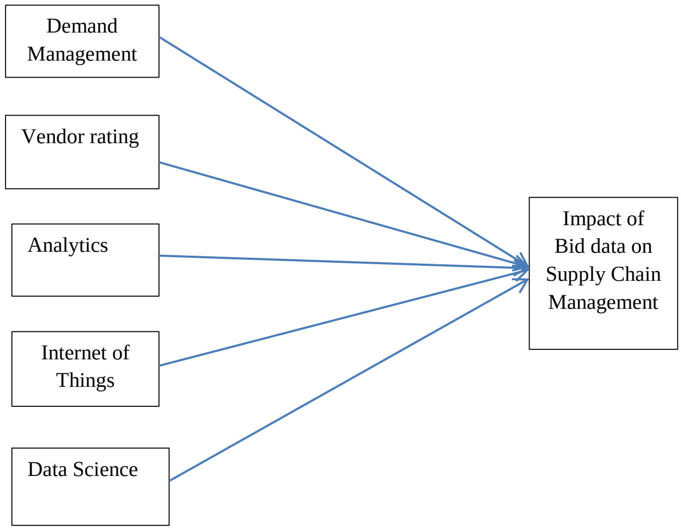

Figure 1. Research framework.

The respondents were chosen based on strong networking with employees of multinational companies with a global presence and having core competence and experience in SCM and IT spread across the United States, the Middle East, Europe, Asia and Australia. The purpose of the research was shared with the respondents to encourage them to take part and a report of the research findings was also offered as an incentive.

The email invitation with the questionnaire was sent to 1006 professionals with strong functional expertise in the supply chain industry and IT. Of these, only 349 professionals (34.6%) responded. Incomplete and unusable entries were omitted from the final data set, leaving 287 (28.5%) usable responses. A summary of the demographic characteristics of the respondents is provided in Table 3.

3.2. Data analysis

Data collected through the primary research (online survey) method were analysed using ADANCO 1.1.1, which is a modelling tool for variance-based structural equations, aiding in developing the research framework and testing the hypotheses (Furrer, Tjemkes, and Henseler 2012). ADANCO uses a composite modelling approach to test hypotheses, which has the advantage of not imposing normality conditions on the data (Gefen et al. 1987). The analysis was performed in two steps: in the first step, the quality of the structural model was estimated; in the second step, the reliability and

Table 3. Breakdown of respondents ($n = 287$) across industry, job level and region.

Item	Measure	Frequency	Percentage
Industry	Manufacturing	186	64.8
	Trade	46	16.0
	Services	55	19.1
Professional level	Junior Executive	54	18.8
	Middle Level Executive	120	41.8
	Senior Executive	50	17.4
	Management Level	63	21.9
Region	Asia	150	52.2
	Australia	33	11.4
	North America	31	10.8
	Europe	33	11.4
	Middle East	40	13.9

validity were measured to determine the best model fit, path analysis was undertaken and the model parameters were estimated (Zikmund 2013).

3.3. Reliability

The reliability of the model fit was determined using Cronbach's alpha, for which a value greater than 0.6 indicates a good level of reliability (Bacon, Sauer, and Young 1995). Composite reliability, which is an indication of integrity and the homogeneity of the model, was measured by Jöreskog's rho (Babakus, Ferguson, and Jöreskog 1987). The statistics for each construct are given in Table 4.

3.4. Convergent validity

Convergent validity measures the indicator variables using conformity scores and examines the construct validity. For each construct, the average variance extracted (AVE) should be greater than 0.5 (Chin 1998). As shown in Table 5, the minimum AVE value is 0.5282 and thus the measurement requirements of the research model are satisfied.

3.5. Discriminant validity

The degree of discrimination between the variables was examined and contrasted with other constructs. The square root of the AVE of a variable should exceed the AVE of the other variables (Fornell and Larcker 1981). Table 6 shows that the model has discriminant validity.

3.6. Saturated and estimated model fit

Regarding model fit, a value of 0.3 denotes a good fit for both saturated and estimated models, whereas a value of 0.1 indicates poor validity. Residual values of between 0.05 and 0.08 indicate a reasonable level of approximation error (Steiger, Shapiro, and Browne 1985). Tables 7 and 8 show the standardised root mean square residual (SRMSR) values of the saturated and estimated models respectively, presenting values within the cut-off of 0.08.

3.7. Structural equation modelling

For structural equation modelling (SEM) in ADANCO 1.1.1 with an unknown population, it is possible to use bootstrapping methods (Efron 1990). The level of significance is tested using t-statistic values. The significance levels in p-values and t-values (Meinshausen and Rice 2006) are given in Table 9.

Five hypotheses were tested in the research and the outcomes were verified against the t-values, as shown in Table 10.

Table 4. Overall reliability of the constructs.

Construct	R^2	Jöreskog's rho (ρ_c) (Composite reliability)	Cronbach's alpha(α)
Impact Of Big Data	0.675	0.901	0.863
Demand Management		0.848	0.732
Vendor Rating		0.817	0.702
Analytics		0.874	0.826
Data Science		0.856	0.747
IOT		0.830	0.693

Table 5. Construct validity.

Construct	Average variance extracted (AVE)
Impact of big data	0.646
Demand management	0.650
Vendor rating	0.528
Analytics	0.536
Data science	0.663
IoT	0.618

4. Research findings

The first hypothesis, H1, addressed the effect of demand management on narrowing the gap between the supply chain and the demand chain. Demand management exhibits a substantial influence (t-value = 1.5453, CI > 90%) and thus H1 ($\beta = 0.0926$, $p < 0.1$) is supported. This indicates that demand management makes a significant contribution to narrowing the gap between SCM and demand chain management through the use of big data tools in the supply chain industry. This is in contrast to an earlier study (Santos and D'Antone 2014), which found no clear evidence of an impact from demand chain management on aligning demand and supply within the firm.

The second hypothesis, H2, concerned the effect on cost savings and low-cost operations from the use of an integrated vendor selection system and criteria coupled with big data technology. The effect of cost savings is highly significant (t-value = 4.0940, CI > 99%). Thus, H2 ($\beta = 0.\ 2571$, $p < 0.01$) is supported. This indicates that vendor rating and selection systems have a significant effect in reducing costs and facilitating low-cost operations in the supply chain industry. However, an earlier study (Masella and Rangone 2000) suggested that vendor selection systems are not exploited to their full potential to yield benefits for customer performance and resource status.

The third hypothesis, H3, examined the effects of analytics on customer demand patterns, which have a significant impact on managing demand in the supply chain industry. Demand management driven by analytics is highly significant (t-value = 7.2448, CI > 99%) and thus H3 ($\beta = 0.5652$, $p < 0.01$) is supported. This indicates that analytics has a significant effect on managing demand in the supply chain industry. However, earlier studies (e.g. Alftan et al. 2015) have pointed to gaps in demand management and centralised forecasting systems targeted at providing better demand management strategies to counter demand fluctuations in the supply chain industry.

The fourth hypothesis, H4, tested the effect of analytics concerning the provision of a greater level of customer satisfaction in the supply chain industry. The effect of analytics is again highly significant (t-value = 4.0815, CI > 99%) and thus H4 ($\beta = 0.3007$, $p < 0.01$) is supported. This indicates that analytics has a significant effect in providing a greater level of customer satisfaction in the supply chain industry. However, earlier studies (e.g. Li and Wang 2015) have pointed to gaps in innovation and technologies aimed at providing better data-driven strategies to improve competitiveness in the supply chain industry.

The fifth hypothesis, H5, examined the effects of data science on vendor rating and the subsequent selection of vendors in the supply chain industry with the help of big data. Once again, this effect is highly significant (t-value = 6.4712, CI > 99%). Thus, H5 ($\beta = 0.5288$, $p < 0.01$) is

Table 6. Discriminant validity.

Construct	Impact of big data	Demand management	Vendor rating	Analytics	Data science	IoT
Impact of big data	**0.646**					
Demand management	0.365	**0.650**				
Vendor rating	0.505	0.329	**0.528**			
Analytics	0.527	0.319	0.506	**0.536**		
Data science	0.405	0.303	0.280	0.365	**0.663**	
IoT	0.489	0.379	0.400	0.435	0.376	**0.619**

Notes: Squared correlations; AVE on the diagonal.

Table 7. Saturated model.

	Value	HI95	HI99
SRMSR	0.072	0.059	0.062
d_{ULS}	1.502	1.002	1.115
d_G	0.697	0.560	0.606

Table 8. Estimated model.

	Value	HI95	HI99
SRMSR	0.124	0.066	0.071
d_{ULS}	4.452	1.266	1.436
d_G	0.896	0.564	0.617

Table 9. Significance levels.

	Significance	*t*-value
Level of significance	$p < 0.1$	1.65
	$p < 0.05$	1.96
	$p < 0.01$	2.59

Table 10. Outcomes of hypothesis testing.

Hypothesis	Effect	Path coefficient (β)	Mean value	Standard error	*t*-value	Supported
H1	Demand management → Impact of big data on SCM	0.0926***	0.09	0.06	1.55	YES
H2	Vendor rating → Impact of big data on SCM	0.2571***	0.26	0.06	4.09	YES
H3	Analytics → Impact of big data on SCM	0.3007***	0.25	0.06	4.08	YES
H4	Analytics → Demand Management	0.5652***	0.56	0.08	7.24	YES
H5	Data science → Vendor Rating	0.5288***	0.53	0.08	6.47	YES
H6	Data science → Impact of big data on SCM	0.3051***	0.16	0.07	2.51	YES
H7	IOT → Impact of big data on SCM	0.2123***	0.22	0.06	3.58	YES

Notes: ***indicates 99.99% significance.

supported. This indicates that data science has a significant impact on vendor rating processes in the supply chain industry. In contrast, earlier studies (e.g. Kumar, Vrat, and Shankar 2006) pointed to the absence of certain important criteria and the vagueness of existing in the vendor selection system in the supply chain industry.

The sixth hypothesis, H6, examined the effects of data science on enhancing operational excellence for stakeholders in the supply chain industry with the help of big data. Once again, this effect is highly significant (t-value = 2.5131, CI > 97%). Thus, H6 ($\beta = 0.3051$, $p < 0.05$) is supported. This indicates that data science has a significant impact on enhancing operational excellence in the supply chain industry. In contrast, earlier studies (e.g. Lee, Padmanabhan, and Whang 2004) pointed to the absence of collaboration and data sharing among retailers and manufacturers, which affects the integration of the entire supply chain mechanism. Moreover, Chen et al. (2000) argued the need for an optimal forecasting method embedded in practical assumptions and real-world complexities.

The seventh hypothesis, H7, argued for the effects of IoT, i.e. RFID, sentiment analysis, etc., on providing real-time data visibility in the supply chain industry via big data analysis. The effect of IoT is once more highly significant (t-value = 3.5764, CI > 99%). Thus, H7 ($\beta = 0.2123$, $p < 0.01$) is supported. This indicates that IoT plays a significant role in providing real-time visibility across the supply chain industry. However, prior studies (e.g. Bardaki, Kourouthanassis, and Pramatari 2012) have suggested that the increased cost of RFID and the delayed adoption of IoT due to privacy issues, as well as inadequate supporting infrastructure and interpretation of data, are the reasons why many firms shy away from the implementation of IoT.

All the research findings concerning the hypotheses are new and comprise improved contributions to the existing body of literature. This is illustrated by the results of the bootstrapped structural model shown in Figure 2, together with the path coefficients depicting significant correlations between the independent and dependent variables.

5. Implications of big data for the supply chain industry and stakeholders

The key factors concerning the use of big data are analytics, IoT and data science, all of which aim to deliver new values to the industry and strongly influence the adoption of big data technology in the supply chain industry. Operational excellence, triggered by big data technology, can increase productivity and help enhance the competitive edge of firms in the supply chain industry. Analytics can increase customer satisfaction and will eventually help retain customers. IOT provides real-time visibility, reflected more broadly across the industry. Cost savings and low-cost operations could be enabled by using better vendor selection systems coupled with qualitative and quantitative analysis of performance using big data tools. Big data can also help in narrowing the gap between the demand and supply chains using data-backed demand forecasts and insights into the buying behaviour of the customer. The adoption of big data technology can create considerable value-added and monetary gain for firms and it will soon become a standard throughout the industry.

5.1. SCOR model

This research provides a new description of the Supply Chain Operations Reference (SCOR) model, incorporating big data and SCM. The SCOR model, as developed by the Supply Chain Council, portrays four essential pillars, i.e. planning, sourcing, making and delivering, which involve the flow of finance, material movement and information flow to integrate demand and supply management across the supply chain. This integration requires proper collaboration and strategic thinking, which involve planning, target setting, monitoring and control (Cai et al. 2009). For optimal utilisation of the system, wastage needs to be eliminated, which will help to reduce costs and generate supply chain surplus. This signals access to relevant and timely information and ensures efficient data management for the regulation of activities and performance (Hoole 2005). The SCOR model is suitable for the evaluation of the financial performance of supply chains and can provide a practical decision support tool for environmental assessment and examining competing decision alternatives along the chain (Ntabe et al. 2015). The original SCOR model is presented in Figure 3.

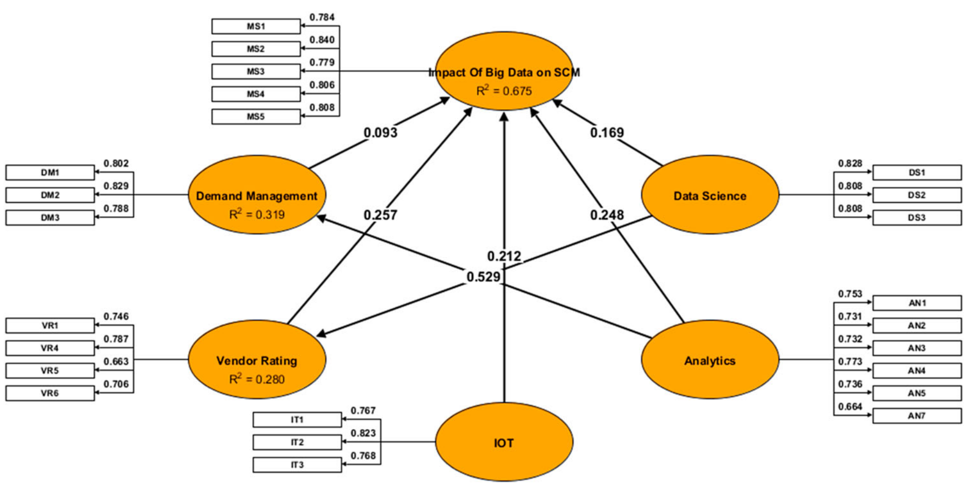

Figure 2. Bootstrapped structural model.

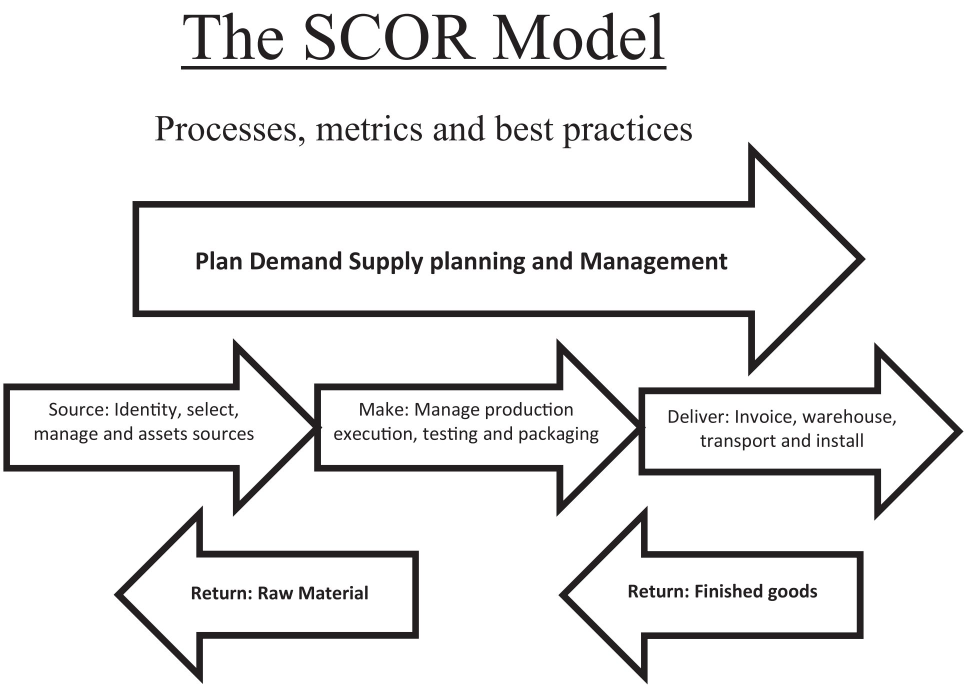

Figure 3. The SCOR model (Supply Chain Council: SCOR 9.0 Overview Booklet, 2008).

Plan

P1:Use big data tools to assess customer demand and needs in real time.
P2: Use“4V” framework consisting of high volume, high velocity, high veracity and high variety information, which uses various processing measures to ensure better decision making.
P3: Use analytics to improve processes and ensure business optimization.

Source

S1: Gather tremendous amounts of data from various processes, i.e., the use of sensors, RFID and tracking devices, which serves as a breeding ground for the generation of big data.
S2: Use social media to rate various vendors.
S3: Use analytic hierarchy processing (AHP) to determine the varying degree of importance of the flow of inputs and provides a strategic perspective in rating suppliers.

Make

M1: Use big data to strengthen market competitiveness and improve data quality management and data usage experience.
M2: Use big data approach to decision making for logistics planning and scheduling using data collected via the use of RFID or sensors on manufacturing shop floors.

Deliver

D1: Use big data to improve visibility by providing an integrated framework to monitor performance and customer interaction through real time data analysis and critical decision-making scenarios, thus mitigating risk and supply chain disruption and failures

Return

R1: Exploit the huge amount of collected data with the help of information technology (IT), i.e., business intelligence insights, analytics, etc., improve existing supply chain practices, reduce costs and provide better inventory management, in turn increase profits in the supply chain industry.
R2: Use demand management to deal with the obsolescence of goods and wastage, especially for perishable goods, for which both agile and lean methodologies may be used.

Figure 4. SCOR model for the application of big data in supply chain management.

This research, by including big data in SCM, provides a new description of the SCOR model, as shown in Figure 4.

6. Conclusions, limitations and scope of future research

This study has focused on the impact of big data on the supply chain industry in terms of its potential to create new value by enhancing operational excellence, enabling cost-saving measures, increasing customer satisfaction and real-time visibility and narrowing the gap between supply and demand chain management, thereby influencing the adoption of big data technology. However, the fact that big data technology is in its nascent stage, together with the initial monetary costs and the lack of knowledge concerning its implementation, hampers its adoption in the supply chain industry. As more firms start to adopt big data technology, the foreseeable associated monetary gains and customer benefits suggest scope for future research concerning these factors to tailor big data technology to demand in the supply chain industry.

Big data technology, coupled with demand management, vendor rating, analytics, cloud computing, IoT and data science, is a key factor in enhancing operational excellence, providing cost savings, customer satisfaction and real-time visibility and reducing the gaps between the demand chain and the supply chain. Our research findings indicate that all these factors provide strong arguments for the adoption of big data technology. These are building blocks that firms can use to build their strategy to innovate, capitalise and monetise values for their firms to ensure that they have a competitive edge over their competitors. Currently, many firms in the supply chain industry are evaluating the financial viability of adopting big data technology and are in the process of making the first move towards harnessing its unique value. Other firms will catch up eventually and big data technology will be adopted across the industry.

Disclosure statement

No potential conflict of interest was reported by the authors .

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