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The impact of supply chain analytics on operational performance: a resource-based view

Bongsug (Kevin) Chae[a], David Olson[b] & Chwen Sheu[a]

[a] Department of Management, Kansas State University, Manhattan, KS, USA

[b] College of Business Administration, University of Nebraska at Lincoln, Lincoln, NE, USA

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The impact of supply chain analytics on operational performance: a resource-based view

Bongsug (Kevin) Chae[a], David Olson[b] and Chwen Sheu[a]*

[a]*Department of Management, Kansas State University, Manhattan, KS, USA;* [b]*College of Business Administration, University of Nebraska at Lincoln, Lincoln, NE, USA*

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This study seeks to better understand the role of supply chain analytics (SCA) on supply chain planning satisfaction and operational performance. We define the architecture of SCA as the integration of three sets of resources, data management resources (DMR), IT-enabled planning resources and performance management resources (PMR), from the perspective of a resource-based view. Based on the data collected from 537 manufacturing plants, we test hypotheses exploring the relationships among these resources, supply chain planning satisfaction, and operational performance. Our analysis supports that DMR should be considered a key building block of manufacturers' business analytics initiatives for supply chains. The value of data is transmitted to outcome values through increasing supply chain planning and performance capabilities. Additionally, the deployment of advanced IT-enabled planning resources occurs after acquisition of DMR. Manufacturers with sophisticated planning technologies are likely to take advantage of data-driven processes and quality control practices. DMR are found to be a stronger predictor of PMR than IT planning resources. All three sets of resources are related to supply chain planning satisfaction and operational performance. The paper concludes by reviewing research limitations and suggesting further SCA research issues.

Keywords: manufacturing management; supply chain management; data mining

1. Introduction

Firms are under heavy pressure to improve supply chain planning and performance because of factors such as increasing uncertainty and competition. Manufacturers have adopted a variety of innovative technological and process-based solutions to obtain and sustain competitive advantage over their competitors. In supply chain management, there is growing interest in business analytics, which is also called supply chain analytics (SCA). SCA refers to the use of data and quantitative tools and techniques to improve operational performance, often indicated by such metrics as order fulfilment and flexibility, in supply chain management (Handfield 2006; Davis-Sramek, Germain, and Iyer 2010; Davenport and O'dwyer 2011; O'dwyer and Renner 2011). There are numerous cases of successful SCA implementation by leading firms. For example, Proctor & Gamble and Walmart are reported to have significantly improved operational efficiency through the use of data and analytical IT tools for supply chain decisions (Davenport and Harris 2007; Davenport and O'dwyer 2011; O'Dwyer and Renner 2011; SAS 2012). Tesco, one of the world's largest retailers, based in the UK, has experienced significant cost savings through SCA over the years (Clark 2013).

Analytics in SCM is not necessarily a new idea (Davenport and O'dwyer 2011), since various quantitative techniques and modelling methods have long been used in manufacturing firms (Turban and Sepehri 1986; Shapiro 2000; Kusiak 2006; Trkman et al. 2010). The recent surge of interest in SCA is accompanied by new challenges and opportunities in both business and information technology (IT) environments. These challenges include issues arising from managing large amounts of data (e.g. data availability and data quality) and dealing with environmental uncertainties (Handfield and Nichols 2004; Liberatore and Luo 2010; Huner et al. 2011; Lavalle et al. 2011; Manyika et al. 2011).

First, IT-based innovations have generated and captured 'more data while also changing the nature of businesses' (Kohli and Grover 2008, 32). For instance, a leading consumer goods firm (Li & Fung) reported the flow of over 100 gigabytes of data through the firm's supply chain network on a given day in 2009 (Economist 2010). The opportunity to gain competitive advantage may thus arise from how firms manage data (Vosburg and Kumar 2001; Forslund and Jonsson 2007; Oliva and Watson 2011). Another major challenge for businesses is the increasing uncertainty in both demand (e.g. consumer market) and supply sides of their businesses. Dealing with demand and supply uncertainty by

*Corresponding author. Email: csheu@ksu.edu

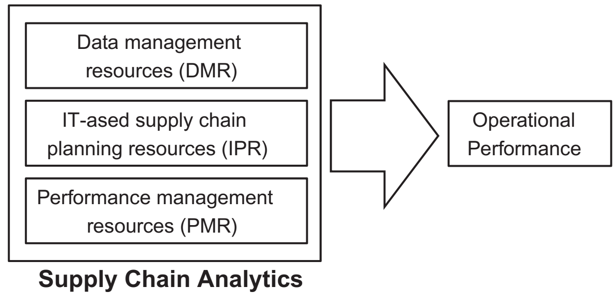

Figure 1. Conceptual model.

means of proper supply chain planning has been a major theme in many recent SCM studies (Oliva and Watson 2011; Demirkan and Delen 2012).

In response to those challenges, SCA has been proposed as a promising approach to better manage data, utilise IT resources and prepare for effective supply chain planning (Handfield 2006; Davenport, Harris, and Morison 2010; Davis-Sramek, Germain, and Iyer 2010; Viswanathan and Sadlovska 2010). This new generation of analytic tools can develop a firm's IT and data management capabilities to enhance planning and improve operational performance (Kohli and Grover 2008; Shapiro 2010; Mithas, Ramasubbu, and Sambamurthy 2011). It is suggested that firms can use SCA from data acquisition (e.g. RFID) and repository (e.g. ERP) technologies to improve supply chain planning through IT-enabled planning and scheduling systems (Davenport and O'dwyer 2011; O'dwyer and Renner 2011). To date, however, there has been very limited empirical research in this data-driven innovative approach to SCM.

SCA research is in its early stage and there is a general lack of theory and of empirical studies. Using the resource-based view (RBV) as the theoretical base, this study expands the understanding of components and performance of SCA. The principal idea of the RBV is that the competitive advantage of a firm lies in its heterogeneous resources, which are valuable, inimitable and non-substitutable (Barney 1991). (Please see Armstrong and Shimzu 2007; Newbert 2007 for a more comprehensive review of empirical research using RBV). Accordingly, we develop a theoretical perspective on SCA as a valuable, inimitable and non-substitutable resource in manufacturing contexts that can be a source of sustained competitive advantage. SCA is a combination of three sets of data and IT-enabled SCM resources, which we refer to as data management resources (DMR), IT-based supply chain planning resources (IPR) and performance management resources (PMR) (Figure 1). Manufacturing firms acquire and use various IT and organisational resources (ORs) in these three aspects of SCA. Firms use diverse analytical and IT resources for acquiring, storing and retrieving data. DMR includes IT-related resources (e.g. RFID and ERP) and analytical capabilities (e.g. mathematical optimization techniques) for data acquisition and management. Also, different software tools (or IPR), from less sophisticated to more advanced, are used for supply chain planning in manufacturers. IPR represents these IT resources (e.g. advanced planning systems) embedding various optimization and predictive analytics (e.g. mathematical programming and statistical analysis). Manufacturers put different degrees of investment in the use of data-oriented process and performance improvement methodologies such as statistical process control and Six Sigma, which are considered PMR.

In this study, these three sets of analytics and IT resources are viewed as complementary, enabling each other. This perspective is developed with reference to the RBV theory, which acknowledges that resources are important for competitive advantage and, in particular, IT-related resources become more effective when combined with non-IT-related resources as complementarities. This study tests hypotheses exploring the relationships among those three dimensions of SCA and the link between SCA and user satisfaction of supply chain planning and SCM performance (e.g. reliability and flexibility). A major contribution of this study is that it offers empirical findings on the relatively new topic of businesses' use of SCA. Particularly, the study's findings shed light on the importance of three sets of complementary IT-enabled resources for successfully taking advantage of business analytics for SCM, the significant role of DMR as the key building block of SCA and the positive impact of SCA on operational performance.

Section 2 reviews relevant literature pertaining to SCA. Three types of IT and ORs are introduced from the RBV perspective. In Section 3, the research model is developed with the hypotheses of the relationships among types of resources and performance variables. The research methodology, including samples and measurements, is discussed in Section 4, followed by the presentation of statistical results in Section 5. Section 6 discusses results, and Section 7 concludes with managerial implications, research limitations and suggestions for future research.

2. Theoretical background

2.1 *Resource-based view*

The RBV holds that resources vary across firms, and differences in resource levels that persist over time enable firms to sustain competitive advantage (Penrose 1959; Wernerfelt 1984; Barney 1991). Under RBV, various technological and organisational practices can be considered resources for acquiring sustained competitive advantage. For instance, organisational knowledge, managerial skills, backend integration, technology and manufacturing facilities are viewed as manufacturer resources (Dong, Xu, and Zhu 2009). Also, diverse SCM-related activities and practices (e.g. supply management practices and environmental management practices) are considered important resources for improving operational performance (Narasimhan and Schoenherr 2012; Blome, Schoenherr, and Rexhausen 2013).

IT is often viewed as a firm resource in the RBV framework (Barney 1991; Wade and Hulland 2004) to create sustained competitive advantage (Barney 1991). Recent studies have studied the role of other resources as complementarities in the effects of IT on firm performance (Powell and Dent-Micallef 1997; Tippins and Sohi 2003; Wade and Hulland 2004; Jeffers, Muhanna, and Nault 2008; Kohli and Grover 2008). Specifically, IT becomes an effective firm resource when it is complemented by other resources or practices (Powell and Dent-Micallef 1997; Tippins and Sohi 2003; Nevo and Wade 2010). Kohli and Grover (2008, 26) argued that 'IT, as simply hardware and software tools, does not create value in isolation, but must be a part of a business value creating process with 'other' IT and organisational factors operating in a synergistic manner'. These 'other' IT and organisational factors are called complementarities. The interaction of IT and complementarities would lead to competitive advantage (Wade and Hulland 2004).

2.2 *Supply chain analytics*

The emergence of new terms, such as SCA, reflects a broad interest in leveraging the business value of supply chain data and harnessing the power of various analytical technologies and methods. Top performing companies are better at utilising their data for business planning and execution (Kiron et al. 2011; Lavalle et al. 2011) and this has led to the increase in supply chain integration and visibility (Viswanathan and Sadlovska 2010; O'dwyer and Renner 2011). In general, academic research expects the benefits of analytics in supporting supply chain operations (Trkman et al. 2010; Davenport and O'dwyer 2011).

Manufacturers have used statistical modelling and optimization (Turban and Sepehri 1986; Shapiro 2000; Chellappa, Sambamurthy, and Saraf 2010; Davenport and O'dwyer 2011) to help deal with supply chain problems (e.g. inventory optimization) on an ad hoc basis. However, the role that SCA plays, regarding both supply and demand factors, is growing in importance and deserves more thorough investigation. Demand factors include the massive amount of data generated from manufacturing activities and customer and supplier interaction, growing competition and uncertainty, and the need for enterprise-level planning on a daily or regular basis. Supply factors include powerful IT for data management and supply chain planning and advanced data-driven techniques for better process and quality control.

2.3 *A RBV of SCA*

In this study, firm resources (e.g. IT) as a source of sustained competitive advantage are used to conceptualise SCA, to test the relationships between different SCA-related resources and to predict their impact on supply chain planning satisfaction and operational performance. Theoretically, *IT-enabled resource* is an RBV-based construct and is supplemented with concepts from systems theory (Nevo and Wade 2010; Nevo and Wade 2011). The concept, defined as 'a system (or a subsystem, depending on one's perspective) comprised of an IT asset and an OR in a relationship' (Nevo and Wade 2011, 405), postulates IT assets as a potential resource for competitive advantage. This conceptual framework asserts that such potential can be realised when IT is integrated with other resources (Nevo and Wade 2010).

Analytics, in general, does not refer to a particular technology, method or practice (Davenport, Harris, and Morison 2010; Trkman et al. 2010; Turban et al. 2011). Rather, it is a combination of multiple IT-enabled resources, which includes both IT assets and ORs, helping the use of 'data, analytical IT, and fact-based management methodologies' (Davenport and Harris 2007) in decision-making. Therefore, SCA is viewed as a combination of *IT-enabled resources* for manufacturing-related data management, supply chain planning and data-driven process and quality improvement. It is a data-driven, analytical decision-making approach to SCM supported by IT resources for data management, supply chain planning and evidence-based management methodologies. These IT-enabled resources would include enterprise IT infrastructure (e.g. ERP and RFID) and analytical methods for data management, technologies embedding optimization and predictive analytics (e.g. mathematical programming) for supply chain planning, and data-driven supply chain ORs (e.g. statistical process control, Six Sigma) for improving manufacturing processes and performance. We give general definitions of three types of SCA IT-enabled resources:

- DMR: Data has long been recognised as a critical asset for organisations (Marchand, Kettinger, and Rollins 2000). The information processing view asserts that 'the greater the uncertainty of the task, the greater the amount of information that has to be processed between decision makers during task execution in order to achieve a given level of performance' (Galbraith 1974, 28). Thus, data management becomes critical for firm performance and IT serves as the infrastructure for data capture, manipulation and redistribution (Fairbank et al. 2006). DMR represents the firm's IT resources for such activities as data acquisition, storage and retrieval. For example, ERP is an IT resource and serves as an integrated, single-instance database for efficient data management providing integrated data for manufacturing planning and control (Su and Yang 2010). Analytic techniques and methods can also be used to generate important manufacturing data or master data (e.g. lead time and batch size). Data management is an important dimension in the quality/process management literature (Flynn, Schroeder, and Sakakibara 1994; Nair 2006; Kaynak and Hartley 2008).
- IPR: IPR represents the *IT resources* embedding various optimization and predictive analytics, such as mathematical programming, simulation, statistical analysis and machine learning algorithms. These analytic techniques and methods are invaluable means for supply chain planning activities, such as master production planning, material requirements planning and capacity planning (Kreipl and Pinedo 2004; Stadtler 2005; Vollmann et al. 2005; Hendricks, Singhal, and Stratman 2007). Supply chain planning software (e.g. Advanced Planning Scheduling) embed these analytics and also have the capability of accessing large data stores (Dehning, Richardson, and Zmud 2007). DMR is important for IPR since the data become inputs for supply chain planning. In general, the more sophisticated those technologies are, the more such analytic methods and data access capabilities are embedded (Singh 2003).
- PMR: While IPR is primarily used for supply chain planning; our use of PMR refers to the firm's resources focusing on closing the gap between planning and execution, through monitoring and correcting manufacturing processes and performance. This is another key area where analytical methods (and technologies) can have positive impacts (Houghton et al. 2004; Yang et al. 2007; Turban et al. 2011). PMR enables analytical thinking and fact-based management. These resources are data-driven SCM practices (Kannan and Tan 2005), often combined with performance metrics (Schroeder 2008), data visualisation of quality problems (Zu, Fredendall, and Douglas 2008) and analytical methods (Scheuermann, Zhu, and Scheuermann 1997). PMR becomes an integral component for SCA, since these ORs help monitor supply chain execution, control performance variability and improve the quality of planning and execution. These resources have been extensively surveyed in the literature (Rungtusanatham 2001; Shah and Ward 2003; Holweg 2007; Shah and Ward 2007; Schroeder 2008; Zu, Fredendall, and Douglas 2008), but with no focus on their data-oriented, analytical aspects.

In summary, these three types of IT and ORs are related and synergistically affect supply chain planning, as well as SCM operational performance. In particular, DMR is expected to serve as the foundation of SCA, since IPR and PMR rely on data as inputs. Advanced IT resources for data management can enable the use of comprehensive and reliable data by IPR and PMR. However, these IT-enabled resources are complementary; DMR, IPR and PMR are not expected to drive performance individually, but, rather, they need to work together.

3. Research model and hypotheses

When SCA is viewed as a combination of IT-enabled resources, we expect there will be interactions among those elements (DMR, IPR, and PMR). Thus, we first consider three internal relationships: (H1) DMR are positively associated with IPR; (H2) DMR are positively associated with PMR; (H3) IPR are positively associated with PMR.

Then, with two outcome latent variables – supply chain planning satisfaction and SCM operational performance – we explore the impact of SCA: (H4a) DMR are positively associated with supply chain planning satisfaction; (H4b) IPR are positively associated with supply chain planning satisfaction; (H4c) PMR are positively associated with supply chain planning satisfaction; (H5a) supply chain planning satisfaction are positively associated with SCM operational performance; and (H5b) PMR are positively associated with SCM operational performance. These hypotheses are presented in Figure 2. The remainder of this section provides the theoretical development of the research hypotheses.

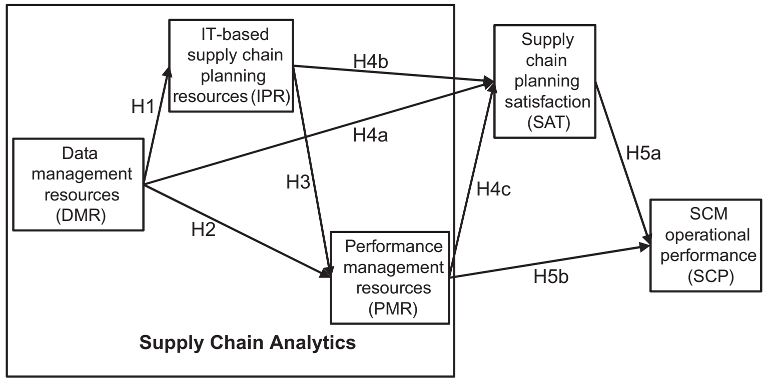

Figure 2. Research model.

3.1 *Linking IT-enabled resources of SCA*

Manufacturing firms have different levels of IT-enabled resources for data management. Some firms possess advanced IT-enabled resources for data management, such as ERP and RFID, that can enable automatic data acquisition, high accuracy in manufacturing-related data quality, and easy data retrieval and use for SCM planning and control. For example, RFID offers many benefits to supply chain management (Sellitto, Burgess, and Hawking 2007) and a major benefit is data acquisition capability (Singh 2003; Delen, Hardgrave, and Sharda 2007). ERP is widely adopted as a centralised data repository (Bendoly 2003; Olson, Chae, and Sheu 2013). Some firms also use sophisticated mathematical models or analytical techniques to determine manufacturing-related master data (e.g. lead time).

IPR involves processing a large volume of production, sales, delivery, and material data for effective planning and scheduling (Gustavsson and Wanstrom 2009; Dionne and Kempf 2011). A centralised corporate repository allows the same data to be used for all types of planning and helps such planning to correctly reflect the company's condition (Hendricks, Singhal, and Stratman 2007). Effective supply chain planning relies on 'informational' efficiency, meaning that data is collected, aggregated, and distributed for the planning process (Oliva and Watson 2011). Performance management practices or resources (PMR), such as quality management and Six Sigma, rely on manufacturers' planning and execution data (Kannan and Tan 2005; Zu, Fredendall, and Douglas 2008). In other words, DMR can be a key contributor to PMR.

As argued by Davenport, Harris, and Morison (2010, 23): You cannot be analytical without data. Data are the basis for both supply chain planning and performance management. Supply chain planning relies on the availability of financial and operational data (Shapiro 2010; Oliva and Watson 2011). Thus, DMR are strongly required prior to IT-based supply chain resources (IPR). For example, IT-based resources for inventory control need to extract data from DMR such as ERP (Stadtler 2005; Vollmann et al. 2005). Also, measuring and improving performance of quality and processes is not possible without access to properly managed data. Thus, quality data and reporting are important for and strongly associated with performance management (Kaynak and Hartley 2008; Mithas, Ramasubbu, and Sambamurthy 2011). Accordingly, we expect that DMR influences the adoptions of IPR and PMR: the adoption of advanced IPR and diverse PMR presupposes the existence of sophisticated DMR.

H1. DMR positively affect IT-enabled supply chain planning resources (IPR).

H2. DMR positively affect PMR.

Manufacturers differ considerably in terms of their analytical capabilities used for supply chain planning activities, such as material planning, inventory control and shop floor control. Some manufacturers possess advanced planning technologies, embedding optimization algorithms, data mining tools and so on. These analytics-embedded IT sources offer several benefits, including reducing planning errors and potential disruption and increasing planning accuracy (Hendricks, Singhal, and Stratman 2007). While IPR might potentially lead to positive SCM outcomes, such as improved on-time delivery (Wu et al. 2006), and financial outcomes, such as profitability (Hendricks, Singhal, and Stratman 2007), in the RBV of IT (Devaraj and Kohli 2003; Wade and Hulland 2004; Kohli and Grover 2008; Nevo and Wade 2010), their value is expected to be attained through complementary resources, PMR.

IPR in general increases visibility and coordination in manufacturing planning and control (Vollmann et al. 2005). This stimulates firms to engage in sensing potential gaps between planning and execution and correcting errors in different areas. For example, IT-based planning reveals forecasting errors, overstocks and other issues, which require coordination to fix. As a result, IPR is expected to increase the need for performance management. Firms are likely to increase relevant resources for performance management. Among previous studies, Martinez-Lorente, Sanchez-Rodriguez, and Dewhurst (2004) suggested that IT resources are positively associated with supply chain practices, such as TQM. Thus, we posit that

H3. IT-enabled supply chain planning resources (IPR) positively affect PMR.

3.2 *Relationships with outcome constructs*

The impact of SCA on firm-level outcomes may be the result of both indirect and direct influences. The RBV of SCA indicates that DMR and IPR are more technological than organisational, while the opposite is true for PMR. Many RBV-based studies suggest that the impact of IT on performance is likely to be indirect, through non-IT factors or resources as complementary resources (Bharadwaj 2000; Wade and Hulland 2004; Devaraj, Krajewski, and Wei 2007; Jeffers, Muhanna, and Nault 2008; Nevo and Wade 2010). Therefore, we consider 'supply chain planning satisfaction (SAT)' as an indicator for planning quality. Satisfaction is the level of favourable 'attitude' (Delone and Mclean 1992; Wixom and Todd 2005) toward supply chain planning. SAT is the measure for the perceived quality or performance of supply chain planning activities.

Accordingly, we expect that each component of SCA positively influences supply chain planning satisfaction. IT resources, such as advanced data repository technology and supply chain planning software, are likely to influence the attitude toward supply chain planning. The literature shows that the quality of data and IT positively influences satisfaction, which in turn results in positive organisational impacts or benefits (Delone and Mclean 1992; Wixom and Todd 2005; Petter and McLean 2009). In addition to DMC and IPR, process and performance management is important to the outcome of supply chain planning. The planning process is influential in supply chain planning performance (De Snoo, Wezel, and Jorna 2011). The implementation of data-driven performance practices has positive effects on planning quality, which in turn leads to operational improvement (De Leeuw and Van Den Berg 2011). As a result, we expect that DMR, IPR and PMR have positive impacts on supply chain planning satisfaction.

H4a. DMR positively affect supply chain planning satisfaction (SAT).

H4b. IT-enabled supply chain planning resources (IPR) positively affect supply chain planning satisfaction (SAT).

H4c. PMR positively affect supply chain planning satisfaction (SAT).

Finally, we expect that supply chain planning satisfaction and PMR positively affect SCM operational performance. DMR and IPR are mostly associated with the usage of information technology, and this leads us to consider their indirect impact on SCM performance. On the other hand, PMR represents more the data-driven, analytical SCM practices or methodologies for improving SCM performance. Therefore, we expect a direct impact of PMR on SCM performance. For instance, studies show that the investment in quality and process improvement practices has positive effects on organisational or supply chain performance (SCP) (Merino-díaz De Cerio 2003). In addition, the literature suggests that satisfaction is linked with positive performance impacts on organisational benefits (Delone and Mclean 1992; Petter and McLean 2009).

H5a. Supply chain planning satisfaction (SAT) positively affects SCM operational performance (SCP).

H5b. PMR positively affect SCM operational performance (SCP).

4. Methodology

4.1 *Data collection*

The research data used in this paper were gathered by the Global Manufacturing Research Group (GMRG), an organisation of international academic researchers studying the effectiveness of manufacturing practices in the supply chain worldwide (www.gmrg.org). The GMRG developed its database using a common survey instrument for all countries. Standardised survey instruments are administered by the GMRG members in their respective countries. Rigorous translating and back-translating rounds were performed by multiple academics to ensure the equivalency, validity and reliability of the questionnaire versions across different languages (Whybark, Wacker, and Sheu 2009). The survey questionnaire was previously validated in many studies published in *Journal of Operations Management*, *International Journal of Production Research*, *Decision Sciences*, among others (Schoenherr 2010; Schoenherr and Narasimhan 2012; Yang, Wacker, and Sheu 2012).

This study uses the data from the GMRG Round 4.0 Survey, which was conducted between 2007 and 2009 (Whybark, Wacker, and Sheu 2009). The manufacturing site or plant formed the unit of analysis, and a total of 537 samples from 15 countries were used in this study (see Appendix A for distribution statistics). The questionnaire was completed by the operations or manufacturing director of the company. Since a single informant from each of the manufacturing firm was asked to complete the survey, concerns of common method variance (CMV) were addressed by Harmon's single factor test (Podsakoff et al. 2003). The un-rotated factor analysis result shows that no single factor accounts for most of the variance and the first factor captures only 33% of the variance, which suggests absence of the CMV problem.

4.2 *Measurement of constructs*

The research model includes constructs related to DMR, IPR, PMR, satisfaction on supply chain plans (SAT) and SCM operational performance (SCP). The scales of these five constructs and descriptive statistics are displayed in Appendix B.

DMR are measured by the level of manufacturers' IT and analytics resources available for three key interrelated aspects of data management: data acquisition, data repository and master data determination. First, there are multiple methods of data acquisition ranging from manual to automatic. RFID is one example of automatic data acquisition in the supply chain. The level of data acquisition resources is measured by how supply chain data, such as inventory transactions and production order status, are acquired. Second, ERP is considered the IT infrastructure for data repository in the corporate world (Bendoly 2003). Therefore, the level of data repository resource is measured by the extent of the manufacturers' investment (money, time and/or people) in ERP. Finally, the level of resources for determining master data is measured by the primary method of determining manufacturing batch sizes, which is an important manufacturing master data.

Supply chain planning involves an array of activities, to include materials, capacity, resources, shop floor operations and so forth (Vollmann et al. 2005). IPR measure the degree of sophistication of IT resources used for various supply chain planning activities. Specifically, this is captured by the type of primary IT resource (e.g. manual system, custom system and commercial system) used for five types of planning: material planning, inventory control, labour planning, shop floor control and cost planning.

PMR measure how extensively the manufacturers' use of data-driven performance management practices impacts quality and process improvement. Examples of these practices include statistical process control, total quality management and Six Sigma. In this study, PMR is measured by the extent of resources invested in three such practices: statistical process control, total quality management and Six Sigma.

The literature shows domain specific satisfaction, such as supplier satisfaction (Benton and Maloni 2005) and customer satisfaction (Acar, Kadipasaoglu, and Schipperijn 2010). Supply chain planning satisfaction (SAT) measures the perceived quality or performance of supply chain planning. Satisfaction can refer to either the satisfaction with specific areas or an overall satisfaction, and could be either a single-item or a multi-item measure (Delone and Mclean 1992). The survey includes five questions about satisfaction with material planning, inventory control, labour planning, shop floor control and cost planning.

Finally, SCP measures the manufacturers' operational performance. Manufacturers focus on different competitive priorities (Ward et al. 2007) and there are diverse measurements for operational performance (Vollmann et al. 2005). This study uses five operational performance measurements: order fulfilment, delivery as promised, delivery flexibility, flexibility to change output volume and flexibility to change product mix.

5. Analysis of the model

Our research model is designed to investigate a relatively new subject in SCM research and practice. There is a general lack of theory and few empirical studies on the topic of SCA. Therefore, the research model is exploratory rather than confirmatory, and the objective is theory building and prediction of construct relationships. This makes Partial Least Squares-Structural Equation Modelling (PLS-SEM) suitable for the analysis of the research model (Gefen, Straub, and Boudreau 2000; Gefen, Ridgon, and Straub 2011; Hair, Ringle, and Sarstedt 2011). The PLS-SEM model reports a two-step process: evaluation of measurements and evaluation of the model (Chin 2010; Hair, Ringle, and Sarstedt 2011; MacKenzie, Podsakoff, and Podsakoff 2011). We used industry type and company size as control variables in this analysis. WarpPLS software was used in this PLS analysis for the evaluation of measurement and model.

Table 1. Composite reliability and average variances extracted (AVE).

Composite Reliability	AVE		DMR	IPR	PMR	SAT	SCP
0.742	0.491	**DMR**	**0.701**	0.438	0.462	0.328	0.054
0.901	0.647	**IPR**	0.438	**0.804**	0.293	0.316	0.006
0.809	0.586	**PMR**	0.462	0.293	**0.766**	0.321	0.271
0.910	0.670	**SAT**	0.328	0.316	0.321	**0.818**	0.211
0.902	0.649	**SCP**	0.054	0.006	0.271	0.211	**0.806**

Note: Square roots of average variances extracted (AVE's) shown on diagonal.

5.1 *Measurement evaluation*

The evaluation of measurement involved two tests: reliability and validity at the individual indicator level and at the construct level. Composite reliability value is a suitable measure of construct reliability for PLS (Hair et al. 2012). The composite reliability coefficients of all five constructs (Table 1) are greater than 0.70, which has been deemed acceptable in prior studies (Fornell and Larcker 1981; Nunnally and Bernstein 1994). Thus, there is strong consistency of construct measurement. Next, combined loadings were examined to access individual indicator reliability (Hair, Ringle, and Sarstedt 2011). Loadings for all the indicators were greater than or at the level of 0.70 (Table 2).

We evaluated the discriminant validity of each construct using two procedures. First, the square root of the average variance extracted (AVE), of each construct, was greater than the construct's squared correlations with other constructs (Fornell and Larcker 1981). Each indicator's loadings were higher than their cross loadings (Chin 2010; Hair, Ringle, and Sarstedt 2011). Finally, convergent validity was accessed by evaluating the AVE. The AVE values of all the constructs are greater than or at the level of 0.50 (Table 1).

5.2 *Evaluation of the PLS model*

The results from evaluation of the PLS model are reported in Figure 3 and Table 3. The result in Figure 3 strongly supports Hypothesis 1 (DMR → IPR). The path coefficient is 0.45, which is statistically significant at the level of 0.01. This supports the hypothesis that DMR, such as data repositories and analytics-based master data management, are associated with the degree of sophistication in supply chain planning technologies adopted by manufacturers. Hypothesis 2 is also supported. The coefficient is 0.42, which is statistically significant at the level of 0.01. This suggests that manufacturers' DMR positively affect the use of PMR. We have also tested the relationships in the other direction (IPR → MR and PMR → DMR). The coefficients for IPR → DMR and PMR → DMR are found to be 0.34 and 0.36 respectively, which are lower than the relationships proposed our original hypotheses (H1: 0.45 and H2: 0.42). In addition, the R^2 0.175 is lower than that of the original model, 0.181.

Hypothesis 3 is supported. However, it is noted that the coefficient, even though it is statistically significant, is relatively weak compared to those of Hypotheses 1 and 2. The three types of IT-enabled resources are positively associated. DMR, an exogenous latent variable in this research model, is shown to positively influence IPR and PMR.

In terms of the impact of SCA on supply chain planning satisfaction, the result supports all three hypotheses (4a; 4b; 4c). This suggests that SCA is likely to enhance supply chain planning satisfaction. Hypothesis 5a, that supply chain planning satisfaction positively affects SCM operational performance, is also supported. The coefficient is 0.15, which is

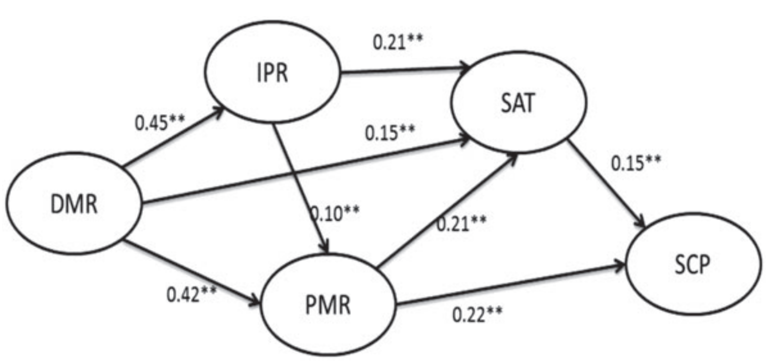

Figure 3. PLS-SEM results.
Note: ** significant at 0.01 level.

Table 2. Loadings and cross-loadings.

Item	DMR	IPR	PMR	SAT	SCP	*P* value
DMR_1	**0.76**	0.06	−0.05	−0.01	−0.04	<0.001
DMR_2	**0.72**	−0.08	−0.15	−0.02	−0.03	<0.001
DMR_3	**0.62**	0.02	0.23	0.04	0.09	<0.001
IPR_1	0.02	**0.82**	−0.03	−0.09	0.03	<0.001
IPR_2	−0.03	**0.83**	−0.01	−0.07	0.05	<0.001
IPR_3	0.03	**0.79**	0.02	0.10	0.00	<0.001
IPR_4	0.05	**0.78**	0.00	0.02	−0.03	<0.001
IPR_5	−0.07	**0.80**	0.03	0.05	−0.05	<0.001
PMR_1	−0.18	−0.05	**0.74**	0.11	0.08	<0.001
PMR_2	0.06	0.00	**0.82**	−0.03	−0.05	<0.001
PMR_3	0.11	0.05	**0.73**	−0.07	−0.02	<0.001
SAT_1	0.01	0.07	−0.07	**0.82**	0.03	<0.001
SAT_2	−0.04	0.07	−0.07	**0.81**	0.06	<0.001
SAT_3	0.04	−0.08	−0.03	**0.84**	−0.01	<0.001
SAT_4	0.03	−0.03	0.04	**0.82**	−0.05	<0.001
SAT_5	−0.05	−0.03	0.14	**0.80**	−0.03	<0.001
SCP_1	0.07	−0.07	0.01	0.04	**0.81**	<0.001
SCP_2	0.04	−0.06	−0.03	0.07	**0.78**	<0.001
SCP_3	−0.03	−0.04	−0.05	−0.01	**0.85**	<0.001
SCP_4	−0.04	0.08	0.07	−0.05	**0.83**	<0.001
SCP_5	−0.04	0.09	0.00	−0.05	**0.76**	<0.001

Note: *P* values <0.05 are desirable for reflective indicators.

Table 3. Summary of hypotheses and results.

H1	DMR → IPR	Supported
H2	DMR → PMR	Supported
H3	IPR → PMR	Supported
H4a	DMR → SAT	Supported
H4b	IPR → SAT	Supported
H4c	PMR → SAT	Supported
H5a	SAT → SCP	Supported
H5b	PMR → SCP	Supported

statistically significant at 0.01. Finally, the result also supports Hypothesis 5b, which explores the role of PMR as complementarities for DMR and IPR: PMR can increase SCM operational performance. Thus, it is suggested that SCA can positively influence supply chain planning and SCM operational performance, regardless of industry type and company size.

6. Discussion and Implications

Drawing from the RBV, this research has explored the relatively new topic of business analytics for supply chain management, representing the *data-driven*, *analytical decision-making approach* to SCM. In particular, we have developed an RVB-based theoretical perspective on SCA as a combination of three sets of IT-enabled resources: data management, IT-based supply chain planning and performance management. We posited that these SCA IT-enabled resources complement one another. According to the RBV literature (Bharadwaj 2000; Wade and Hulland 2004; Devaraj, Krajewski, and Wei 2007; Jeffers, Muhanna, and Nault 2008; Nevo and Wade 2010), it has been proposed that more technological resources, such as DMR and IPR, positively affect SCM performance through more ORs (PMR) as complementarities. The overall results support these claims and also indicate the positive impact of SCA IT-enabled resources on SCM performance.

6.1 *Relationship between DMR, IPR and PMR*

The statistical results support the proposition that data management is critical for the manufacturer in deploying SCA. We find that DMR play an important role in supporting IPR and PMR. This implies that manufacturers with high DMR are likely to be using advanced planning resources and more PMR.

These findings shed light on the importance of firms' DMR for SCM activities and performance. Few studies have empirically examined the impact of DMR on SCM. In this sense, DMR should be considered a key building block of manufacturers' business analytics initiatives for supply chains. Data has great potential to be transformed to create business value for manufacturers (Marchand, Kettinger, and Rollins 2000; Chae, Yen, and Sheu 2005; Davenport, Harris, and Morison 2010; Lavalle et al. 2011; Mithas, Ramasubbu, and Sambamurthy 2011). It appears that the value of data is transmitted to outcome values through increasing supply chain planning and performance management capabilities. The investment and effort of acquiring DMR is definitely worthwhile for manufacturers.

The operations management literature has explored the role of analytical information technologies and mathematical modelling methods for supply chain planning (Shapiro 2000; Stadtler 2005; Vollmann et al. 2005; Trkman et al. 2010; Oliva and Watson 2011). We have viewed these IT-enabled resources as one of the integral components of SCA. Our results support the supposition that these planning resources are largely dependent upon data resources (DMR → IPR): manufacturers with high DMR tend to have sophisticated planning resources. The SCM and IT literature has assumed this large role of data management for supply chain planning technologies. Our findings confirm that the deployment of advanced IPR is likely after the acquisition of DMR.

We also find that IPR positively affects PMR. This implies that manufacturers with sophisticated planning technologies would be better able to take advantage of data-driven process and quality and process improvement practices, such as Six Sigma and statistical process control, than those with primitive planning technologies. However, the coefficient of DMR → PMR (0.43) is found to be much stronger than that of IPR → PMR (0.11). Similar to the findings from the literature on quality improvement (Laframboise and Reyes 2005; Zu, Fredendall, and Douglas 2008) and information management (Mithas, Ramasubbu, and Sambamurthy 2011), DMR is shown to be a stronger predictor of the degree of PMR than IPR.

In summary, our RBV of SCA has introduced three types of resources – DMR, IPR and PMR – and proposed relationships among them. The results indicate that those resources are distinct, yet related, as proposed. In other words, a manufacturer's data management capability would be a good indicator of the level of its IT-based supply chain planning and performance management capabilities. In addition, IT-based planning capability can predict the level of performance management capability. It is evident that firms invest in DMR with the expectation of quality and comprehensive data, which are the necessary input to IPR and PMR in practice. This leads to increases in IPR and PMR. Furthermore, more IT-based analytical planning opens the needs and opportunities for data-driven process and quality improvement. Thus, both theoretical discussion and practical application of business analytics for supply chain should consider those three types of resources as a whole for SCA, rather than treating them as separate entities.

6.2 *Relationship between SCA IPR, SAT and SCP*

There is empirical support that SCA positively impacts outcome variables: supply chain planning satisfaction (SAT) and SCM performance (SCP). We find that all three sets of IT-enabled resources (DMR, IPR and PMR) have a positive impact on supply chain planning satisfaction (SAT). Furthermore, SAT positively affects SCP (SCM operational performance). Apparently, these SCA resources are helpful for improving planning quality, which is positively associated with operational performance.

On the other hand, the correlation of DMR and IPR with SCP is found to be statistically insignificant (Table 4). This implies that IT-enabled resources for data management and supply chain planning are important, but do not seem to create business value themselves. Instead, DMR and IPR, which are more technological resources for SCA, have an *indirect* impact on SCM performance through complementary resources, PMR. This finding suggests at least two important implications.

First, the RBV-based perspective on SCA, as a combination of three types of data-driven and analytical IT and ORs, offers a more theoretically suitable view than what would be a popular, technological view focusing on either data management capability or supply chain planning capability. Without this integrative view, different (potentially incomplete or even wrong) conclusions can be reached: for example, an investment in analytical resources for planning alone has led to improving operational performance.

Table 4. P values for correlations of latent variables.

	DMR	IPR	PMR	SAT	SCP
DMR	1.000	<0.001	<0.001	<0.001	**0.209**
IPR	<0.001	1.000	<0.001	<0.001	**0.883**
PMR	<0.001	<0.001	1.000	<0.001	<0.001
SAT	<0.001	<0.001	<0.001	1.000	<0.001
SCP	0.209	0.883	<0.001	<0.001	1.000

Next, data-driven organisational practices (e.g. statistical process control and Six Sigma), which aim to close the gap between planning and execution through process and quality improvement (Houghton et al. 2004; Yang et al. 2007), are critical, in that they are complementary to technological SCA resources (DMR, IPR) and they have a *direct* impact on SCM performance. This aligns with the increasingly common perspective on IT value from RBV (Tippins and Sohi 2003; Kohli and Grover 2008; Nevo and Wade 2010). As noted earlier, IT resources for data management (and analytical planning) are critical for SCA. However, it can be claimed, from the RBV of SCA, that those IT resources can be effective only when they are combined with data-driven organisational practices. This interaction of IT and ORs leads to performance improvement.

7. Conclusion: managerial implications and future research

The extensive use of SCA is a relatively new innovation in SCM practice. This research has been exploratory and theory building. While there is growing interest in SCA (Shapiro 2010; Davenport and O'dwyer 2011; Jander 2011; O'dwyer and Renner 2011), there is a lack of theory or theoretical framework to study SCA and its impact on SCM performance. This led us to develop a theoretical framework for SCA and identify relevant latent variables and indicators for empirical research.

The results from this exploratory research have several implications for practice. First, there is much discussion among academics and practitioners about the use of business analytics for supply chain management, and the opportunities and challenges this new SCM innovation offers. Anecdotal evidence holds that the use of business analytics is positively associated with organisational performance. The important question is whether the use of analytics for supply chain management is just hype or if it has a real effect in enabling performance improvement. Our research indicates that the positive impact of analytics on SCP could be real.

The perspective on analytics for supply chain management (or SCA) in this research goes beyond a single technology (e.g. APS and ERP) or methodology (e.g. optimization modelling and Six Sigma). Even the proposed perspective is not limited to analytical IT resources alone. Rather, this research has drawn upon an established body of the RBV literature on IT and the impact of IT, and formulated a view of SCA as a combination of IT-enabled resources, including IT assets, analytical methods and evidence-based methodologies. Thus, managers are discouraged from taking the simplistic view that a single analytical IT or data management tool alone would create business value. Instead, they should consider a combination of various IT-enabled resources for data management, analytical and modelling methods and fact-based methodologies. This can lead to a systematic investment in those SCA IT-enabled resources, resulting in competitive advantage and performance improvement. Specifically, each set of IT-enabled resources is found to be important for improving operational performance: DMR is posed to be the key building block of SCA; IPR is driving for greater planning satisfaction and enabling the adoption of PMR, which have been found to be important complementarities in the implementation of SCA in practice.

Finally, there is room for improvement of the research model. One potential improvement is to include additional latent variables or items in the research design. Our research model included three latent variables (DMR, IPR and PMR). Other firm resources or capabilities could be included in future research models. Other potential latent variables or items would be leadership, organisational structure, analytical skills and partner support (Pfeffer and Sutton 2006; Dong, Xu, and Zhu 2009; Davenport, Harris, and Morison 2010; Oliva and Watson 2011). For example, manufacturers' management leadership and culture could be good ORs for SCA. Manufacturers operate their supply chains with a large network of partners, who become the source of the data used for supply chain planning and performance management. Therefore, the partners' IT resources for data sharing could be considered in the future research design. Furthermore, the data were collected between 2007 and 2009 (Whybark, Wacker, and Sheu 2009). While we have no evidence to believe the relationships among those variables in the model have had significant changes in the last three or four years, the proposed model should be validated with more recent data in the future. Overall, the current research design and its findings offer vital information to better understand the role of business analytics for supply chain management and its impact on operational performance.

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Appendix A. Distribution of industries and firm size

(a) Firm size

Size	Frequency	Percentage (%)
(1) ≤50 employees	116	21.6
(2) 51–250 employees	206	38.3
(3) ≥251 employees	180	33.5
N/A	35	6.5
Total	537	100.0

(b) Industry

Industry	Freq.	Percent (%)	Industry	Freq.	Percent (%)
Electronic and other Equipment	104	19.4	Motor vehicles, trailers and semi trailers	15	2.8
Industrial machines and computer equipment	74	13.8	Other manufactured transport equipment	11	2.0
Fabricated metal	55	10.2	Apparel and Other finished Products	11	2.0
Food Products GMP	37	6.9	Printing and Publishing and Allied Industries	10	1.8
Textile Mill Products	32	6.0	Paper and allied products	10	1.8
Stone clay glass and concrete products	26	4.8	Miscellaneous Manufacturing	98	18.2
Furniture and fixtures	21	3.9	Total	537	100.0
Rubber and Plastic products	18	3.4			
Chemical and allied products	15	2.8			

Appendix B. Detailed information on constructs.

Construct: DMR	Mean	SD
(1) Method of recording data: *manually written or typed on paper files/manually typed into computerized system/bar codes/automatic data capture using RFID, etc.*	2.378	0.775
(2) The primary way of determining manufacturing data such as manufacturing batch size: *experience/statistical methods/mathematical optimization*	1.749	0.764
(3) Degree of investment in centralized data repository such as ERP. *1: not at all – 7: to a great extent*	4.149	1.830
Construct: IPR		
(1) How is material planning (e.g. Material Requirement Planning, MRP) performed?	3.182	1.402
(2) How is inventory control (e.g. Quantity/location accuracy) performed?	3.264	1.302
(3) How is labor planning (e.g. Capacity Requirements Planning) performed?	2.492	1.416
(4) How is shop floor control (e.g. Production Activity Control) performed?	2.646	1.432
(5) How is cost planning performed? *0: no formal system. 1: manual. 2: desktop software. 3: custom software. 4: commercial software. 5: modified commercial software*	3.022	1.320
Construct: PMR		
(1) Extent of invested resources in TQM	4.587	1.695
(2) Extent of invested resources in statistical process control	3.842	1.802
(3) Extent of invested resources in six sigma. *1: not at all – 7: to a great extent*	2.927	1.995
Construct: SAT		
To what extent are you satisfied with your current		
(1) Material planning	4.680	1.520
(2) Inventory control	4.791	1.538
(3) Labor planning	4.298	1.527
(4) Shop floor control	4.501	1.510
(5) Cost planning. *1: very dissatisfied – 7: very satisfied*	4.674	1.517
Construct: SCP (SCM performance)		
Compare the performance with your major competitors		
(1) Order fulfillment	5.266	1.225
(2) Delivery as promised	5.264	1.182
(3) Delivery flexibility	5.356	1.145
(4) Flexibility to change output volume	5.117	1.212
(5) Flexibility to change product mix. *1: far worse – 7: far better*	5.091	1.257