International Journal of Information Technology & Decision Making
Vol. 12, No. 1 (2013) 9–26

DOI: 10.1142/S0219622013500016

BUSINESS ANALYTICS FOR SUPPLY CHAIN: A DYNAMIC-CAPABILITIES FRAMEWORK

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Supply chain management has become more important as an academic topic due to trends in globalization leading to massive reallocation of production related advantages. Because of the massive amount of data that is generated in the global economy, new tools need to be developed in order to manage and analyze the data, as well as to monitor organizational performance worldwide. This paper proposes a framework of business analytics for supply chain analytics (SCA) as *IT-enabled, analytical dynamic capabilities* composed of data management capability, analytical supply chain process capability, and supply chain performance management capability. This paper also presents a dynamic-capabilities view of SCA and extensively describes a set of its three capabilities: data management capability, analytical supply chain process capability, and supply chain performance management capability. Next, using the SCM best practice, sales & operations planning (S&OP), the paper demonstrates opportunities to apply SCA in an integrated way. In discussing the implications of the proposed framework, finally, the paper examines several propositions predicting the positive impact of SCA and its individual capability on SCM performance.

Keywords: Business analytics; analytical IT; sales & operations planning; dynamic capabilities.

1. Introduction

A recent report[1] based on interviews with executives of global companies offers several findings, two of which deserve special attention. First, the corporate world faces a deluge of data. Executives note that the volume of data in their firms is soaring. For example, a well-known supply chain player for consumer goods reported a flow of over 100 gigabytes through the company's supply chain network on a particular day in 2009.[2] This "big data" is recognized elsewhere as well.[3]

Second, the response to this deluge seems to have a great deal of influence on firm performance. Top-performing firms are more likely to be involved in using the data for better operational and strategic decision making. Top-performing companies are also more likely to utilize supply chain intelligence that aims to collect and analyze the data from their supply chain operations, in order to increase supply chain visibility and integration.[4]

In response to these business environments, there is a growing recognition of the value of advanced analytic tools and applications in supply chain operations.[4–10] A recent study[8] suggests a positive relationship between business analytics (BA) and supply chain performance. This positive impact of BA for supply chain management may be even greater in uncertain business environments.[9] Various terms such as "Supply Chain Intelligence" and "Supply Chain Analytics (SCA)" have become common in both industry and academia.[11] Despite this growing interest in the application of BA for supply chain, to our knowledge there is no adequate framework within which to understand the role of SCA and to actualize this new innovation in practice.

In response to this lack of a practical framework, this paper proposes a framework for understanding how BA can support supply chain organizations. This framework describes BA for supply chain (or SCA) as IT-enabled, analytical dynamic capabilities for managing data, supply chain processes, and supply chain performance. This dynamic-capabilities view of SCA is drawn upon the management and IT literature on dynamic capabilities.[12–15]

The paper first presents a short survey of the literature on BA. Next, it offers a dynamic-capabilities framework for SCA. This involves a dynamic-capabilities view of SCA and a proposed set of SCA integrating data management capability (DMC), analytical supply chain process capability (APC), and supply chain performance management capability (SPC). The following section uses Sales & Operations Planning (S&OP) and demonstrates how the potential of SCA is actualized in practice. In discussing the implications of the proposed framework, the paper proposes several propositions predicting the positive impact of SCA.

2. Background: Business Analytics

Many definitions of BA can be found in both academic outlets and industry press and there are similar and/or competing terms such as business intelligence (BI). In this paper, BA and BI are viewed similarly in that both terms reflect a need for building and utilizing various analytical capabilities for organizational business processes and decision support. INFORMS[16] gives a concise definition of BA: "Analytics facilitates realization of business objectives through reporting of data to analyze trends, creating predictive models for forecasting and optimizing business processes for enhanced performance."

BA is viewed as a broad range of technologies, analytical techniques, and methodologies which are combined to support business decision making.[17] Specifically, a firm's BA consists of three components: databases (also called as data warehouses), analytical IT embedded data mining[10] or other knowledge discovery techniques, and business performance management (BPM). This view of BA is close to another definition of BA as "the use of data, analytical IT, and fact-based management methodologies."[18] Data, analytical IT and BPMS are integral components of BA, all of which enable each other. For example, data use enables planning and analysis.

First, data management is the key building block of BA. BA aims to find "intelligence" within large volumes of the firm's data about products, services, customers, manufacturing, sales, purchasing, and so on. Thus, the inputs of BA activities are the data stored in various corporate databases. Most data in these corporate databases are transaction-oriented (e.g., purchasing, order, sales, delivery), which is not suitable for data analysis and reporting without processing. Thus, data integration or transformation through ETL (extract, transform, and load) becomes an important technical issue for a firm's database management[19] and companies often use a data warehouse — a centralized storage location for a variety of transactional data (often in an Enterprise Resource Planning System) — for querying, reporting, and analysis.[20] The capability for managing data positively influences organizational performance.[21]

Second, the data must be utilized to create business value. Different data mining (or knowledge discovery) techniques[22,23] and prescriptive analytical techniques (e.g., mathematical optimization) are used to analyze the data to find useful information such as prediction of customers and sales, objective function, business constraints, etc. Data mining techniques can be categorized in three broad approaches: predictive modeling (to include classification), clustering, and association.[17,24] In particular, those who practice predictive modeling or analytics, an approach that has received much attention recently, are developing a statistical (e.g., regression[25] or AI-based model[26] to predict future events or cases based on historical data. In addition to predictive analytics, there is another type of analytics, prescriptive analytics, which includes mathematical optimization,[27] simulation,[28] etc. These diverse predictive and optimization analytics are embedded in analytical supply chain planning technologies such as advanced planning scheduling (APS).[29] Increasingly, these analytics are embedded in supply chain planning technologies.[29] These technologies positively affect plant performance.[30]

Lastly, BPM is a crucial component of BA, enabling three broad sets of activities in any business: monitoring, reporting, and correcting. BPM is like feedback in open systems.[31] Various techniques, tools, and processes are used for those three BPM activities. For example, firms use key performance indicators (KPIs) and other metrics to "monitor" their performance in various areas (e.g., finance, marketing, supply chain), technologies for "querying and reporting", and methodologies such as Six Sigma for correcting (or improving) the situation. An example of performance measurement is balanced scorecard.[32] The balanced scorecard has been applied to measure performance within supply chains.[33] For monitoring and reporting, firms are using various dashboard and scoreboard technologies.[34] Correcting utilizes systematic approaches to identify root causes and develop ideas for improvement. An example is Samsung's Six Sigma-based innovation for supply chain.[35]

3. SCA: A Dynamic-Capabilities Framework

Despite the increasing interest, SCA is an under-defined construct. The proposed framework of SCA involves three parts: first, the framework offers a dynamic-capabilities view of SCA (Sec. 3.1); second, it contains a set of SCA including three dimensions (Sec. 3.2); third, it presents a set of propositions for predicting the impact of SCA on supply chain performance (Sec. 5). In addition, the proposed framework of SCA is illustrated through S&OP (Sec. 4).

3.1. *SCA as IT-enabled, analytical dynamic capabilities*

The dynamic capabilities view of firms has received much attention in recent years.[13,15,36] The concept was developed from the management literature and rooted in the resource-based view of competitive advantage.[13,36] Dynamic capabilities are defined as "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (see Ref. 12, p. 516). As shown in this definition, the literature has recognized dynamic capabilities as viable means for managing business challenges in turbulent environments.[15]

In the management literature, dynamic capabilities explain how certain firms outperform others and experience competitive advantage.[12,37] IT literature has focused on investigating how ITs can be leveraged for dynamic capabilities. Studies indicate that IT-leveraged dynamic capabilities lead to increases in operational performance such as new product development.[14,15] Dynamic capabilities are the high-order capabilities and thus can be disaggregated into different capacities,[37] such as the capacity for improving quality, the capacity for managing human resources, and the capacity for utilizing technologies.[38]

Drawn from the concept of dynamic capabilities, SCA is defined as IT-enabled, analytical dynamic capabilities for improving supply chain performance. There are different types of dynamic capabilities within firms.[15] The purpose of SCA, as dynamic capabilities, is to manage supply chain effectively and efficiently in competitive environments. SCA are dynamic capabilities leveraging the firm's IT and analytical capacity.

SCA can be disaggregated into the capability for managing data, the capability for supporting supply chain processes, and the capability for monitoring supply chain performance (Fig. 1). SCA is for gaining useful information from supply chain data and applying such information to planning, execution, and evaluation processes. It relies on an extensive use of data management and analytical IT resources. It also involves the fact-based management of supply chain through supply chain metrics and performance management processes. These three capacities are not mutually exclusive. Instead, they are enabling each other: for example, data enables analytic supply chain processes and performance management.

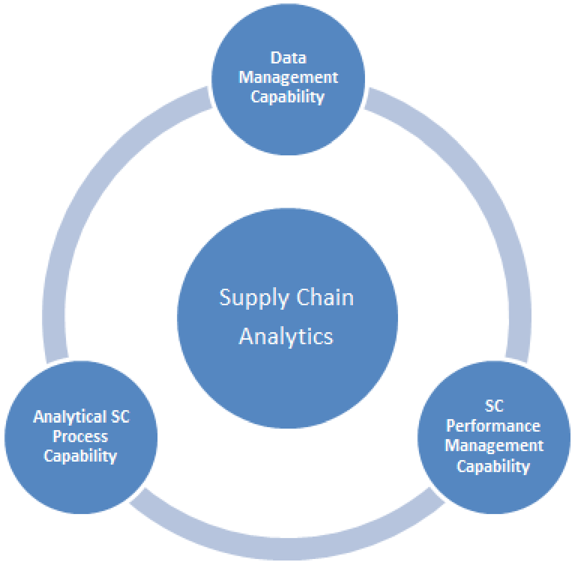

Fig. 1. Supply chain analytics (SCA).

3.2. *A proposed set of SCA*

3.2.1. *Data management capability (DMC)*

Data management is the backbone of SCA. Supply chain operations generate tremendous amounts of data. A manufacturer's supply chain planning and control alone require the collection and processing of large volumes of data.[39] Supply chain coordination practices such as collaborative planning, forecasting and replenishment (CPFR) or vendor managed inventory (VMI) add even more to the data to be tracked. Business to business data improves supply chain operations and performance.[40] DMC is the IT-enabled capability of data acquisition and transformation. Firms need to possess the capability to store and manage data and to provide access to the data for supply chain operations and performance management activities. This capability is enabled by database and analytical technologies.

Capability of data acquisition/repository: Supply chain data requires advanced data storage systems. For example, Wal-Mart has relied upon modern data management to gain competitive advantage in supply chain and inventory management, making it one of the most profitable business organizations in the 20th Century (and this century as well). Wal-Mart has invested in one of the largest private data management systems in the world.[41]

The technologies that are available for supply chain data collection/storage include ERP, inter-organizational systems (IOS), RFID, etc. A popular IT resource for data storage today is ERP, which often serves as a centralized data repository or data IT infrastructure. Among many benefits, ERP has become a key enabler of data management for supply chain through enterprise-level data acquisition and real-time data access by decision makers.[42,43] IOS has facilitated data sharing between companies.[44] For example, web-based EDI supports data acquisition from suppliers and customers and increases data integration.[45] An emerging IT resource for data acquisition is RFID. RFID enables real-time data acquisition and increases data accuracy.[46] As a result, there are many potential benefits of RFID as an IT resource for supply chain data acquisition.[26,47]

Capability of data transformation: Data is collected through RFID, web-based EDI, and ERP for transactional reasons. But there are many opportunities to utilize this data, supplemented by external data, for visualization, Online analytical processing (OLAP) analysis, and data analysis. Business analysis can draw upon data collected in intra-organizational systems (e.g., ERP), as well as gathered data from external sources (e.g., web-based EDI). Data transformation is a key element in the business analytic process. Data needs to be consolidated in order to maximize its usefulness. OLAP and data warehouses are examples of IT resources for transforming transactional data to analytical data for supply chain planning and performance management.

Data warehouses (and smaller variants, data marts) often integrate information from a variety of places.[48] Data exists in internal operational systems and external data sources. Thus, data needs to be integrated. The process of integrating data often reveals various data quality issues (e.g., inaccuracy, redundancy).[49] In response, data needs to be explored and pre-processed (e.g., cleaned, re-organized) before it can be used for analysis and reporting.

OLAP is a multidimensional approach to organizing data for further analysis.[50] OLAP takes data from different data storages and transforms them into multidimensional forms.[51] This allows users to access data from multiple perspectives, and to answer diverse business questions through exploratory data analysis.

3.2.2. *Analytical supply chain process capability (APC)*

A manufacturer's supply chain can be viewed as a series of four processes: plan, source, make, and delivery (Fig. 2).[52] These four processes have significant roles in facilitating supply chain activities and improving the overall business performance.[53–55] There is much potential to deploy analytical techniques

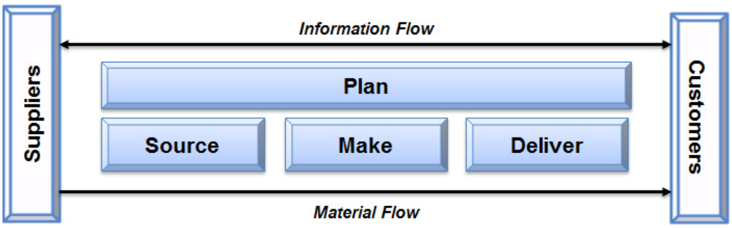

Fig. 2. Supply chain processes.

(prescriptive and predictive analytics) and IT resources embedding those techniques in those four processes.[8,29,56,57] Firms need to possess the analytical capability to handle supply chain processes.

Innovative analytical techniques have been proposed for these processes, to include simulation[58] (e.g., Data Envelopment Analysis and PROMETHEE II multi-criteria models)[59] and data management tapping transactional data to automate SCOR monitoring.[60] These analytics can be leveraged further for APC.

Analytical capability for planning: Plan is "gathering customer requirements, collecting information on available resources, and balancing requirements and resources to determine planned capabilities and resource gaps" (see Ref. 52, p. 13). In other words, the Plan process focuses on "analyzing data to predict market trends of products and services" (see Ref. 8, p. 2) and developing supply plans to match market demands.

Analytical IT resources can play two major roles in the Plan process: demand planning and supply planning. Demand planning is a critical function, as it aims to predict future demands and, thus, predictive data mining techniques, including time series and causal analysis, are useful for forecasting sales volumes and also for profiling potential consumers accurately.[17] In practice, predictive analytical methods (e.g., neural network, support vector machines) have proven to be effective tools for demand forecasting.[61,62] In addition, prescriptive analytics such as stochastic optimization models are useful for supply chain planning. Price optimization using both predictive and prescriptive analytics is also important in demand planning.[63] The analysis of large sets of historical sales data helps to find patterns in consumer purchase behaviors. This pattern discovery, combined with optimization models, enables dynamic pricing changes over time.

The goal of supply planning is to match customer demands with resources in a profitable manner. A supply chain needs to consider a broad range of activities, including sourcing and production from a planning perspective. The desired outcome is a financially optimized production plan that satisfies market demands and adequately utilizes internal and external resources. The majority of analytical IT for supply chain planning embeds prescriptive analytics capabilities. In particular, linear programming-based optimization[64] is popular in APS systems.[65] Additionally, predictive analytics using genetic algorithm, neural network, and fuzzy programming techniques can be effective for developing supply planning and synchronizing production, source, and demand.[61]

Analytical capability for sourcing: Source is necessary for successful Plan through "issuing purchase orders, scheduling deliveries, receiving shipment validation and storage, and accepting supplier invoices" (see Ref. 52, p. 13). The primary role of analytical IT for sources lies in "improving inbound supply chain consolidation and optimization" (see Ref. 56, p. 229). Broad applications include "the use of an agent-based procurement system with a procurement model, search, negotiation and evaluation agents to improve supplier selection, price negotiation and supplier evaluation and the approach for supplier selection/evaluation" (see Ref. 8, p. 2).

There is a strong application for the use of analytical IT to support supplier selection within supply chains.[66]

IT with prescriptive analytics has long been a key enabler of manufacturer's sourcing-related decision making.[55] Predictive analytics techniques are increasingly available these days for intelligent material planning, inventory management, and supplier relationship management. For example, classification data mining techniques such as SVM[67] and case-based neural network[68] are promising as tools to enable effective sourcing. Adopting these advanced analytics can make the sourcing process intelligent, thereby doing away with the need for the formulation of the detailed decision-making process now used by purchasing managers.[67] Pattern recognition, when used with large sets of historical purchase orders (PO) and supplier delivery data, can reveal hidden facts and potential problems with internal sourcing processes and supplier delivery performance. All data mining tools have potential to support every application area. Tools deal with mathematical models of problems, and value comes from applying these tools through different views, reflecting specific applications.

Analytical capability for making: Make describes "the activities associated with the conversion of materials or creation of the content for services",[52] what is broadly called manufacturing and production at factory level. One of the critical activities is "the correct production of each inventory item not only in terms of time, but also about each production belt and batch" (see Ref. 8, p. 2). IT resources can potentially play a role in various areas such as predicting machinery failure, identifying anomalies in production processes, and discovering hidden patterns and potential problems (see Ref. 17, p. 146). The analysis of these production-related problems relies heavily on the data, which usually comes from manufacturing execution systems (MES). There are many real-world applications for prescriptive and predictive analytics in the processes, including aluminum processing, semi-conductor manufacturing, electronic assembly, and DNA manufacturing.[69]

Specifically, prescriptive and predictive analytics techniques such as Genetic Algorithm (GA) are useful for various production-related planning problems such as lot-sizing, lot-scheduling, and optimizing the sequence of orders in manufacturing line.[61] The mathematical models based on learning algorithms can handle the complexity involved in daily production scheduling, as shown in the application of GA for manufacturing at John Deere.[70] In addition, clustering methods such as k-means are effective for finding out potential root causes of faults and process variations in production systems.[71] Association rule mining (e.g., *a priori* Algorithm) can help identify potential reasons for machine failures and the impacts of such failures on production efficiency and product quality.

Analytical capability for delivering: Deliver includes "the activities associated with the creation, maintenance, and fulfillment of customer orders".[52] This includes repetitive activities such as order creation, order batching, ship consolidation, carrier selection and evaluation.[72] The role of BA is to improve the efficiency and effectiveness of outbound material flow[56] by delivering products to customers and markets more efficiently.[8] This BA application is also called intelligent order management or "logistics intelligence".[63]

Order batching and delivery scheduling are important tasks in distribution. Predictive analytics are helpful in analyzing and segmenting orders and deliveries in terms of different measures (e.g., profitability, location, costs). Thus, clustering methods (e.g., Self-Organizing Map) can be used to determine the best ways of delivering products in terms of profitability and optimization of supply chain.[72] Association mining can also aggregate orders in distribution centers based on their associations, thus making the movement of order efficient. Prescriptive analytics models using forecasting methods can help predict future orders and delivery demands by different categories (e.g., countries, regions, distribution centers). GA-based models and fuzzy logic can be applied to various delivery processes including logistics network design/planning and vehicle routing/assignment.[61]

The APC is enabled by these analytical techniques. Many of these analytical techniques mentioned above are developed as individual "analytical apps."[73] These "analytical apps" are used for specific problem domains, for example, an analytical software tool for detecting machine failure. They used to be operated independently (not integrated with other apps or systems), on a small scale. Now these analytical techniques are becoming increasingly available with analytical IT resources, such as APS systems, MES, order management systems, and logistic information systems. There are many opportunities for future developments in analysis and technology to improve supply chain processes.

3.2.3. *Supply chain performance management capability* (*SPC*)

High-performing supply chains require performance measurement capabilities.[31,33,35,74] Effective supply chain performance management system (PMS) relies on analytical and data-driven methodologies and technologies as shown in the studies of Samsung SCM Group,[35] Western Digital,[34] and other companies.[75] One example is Samsung, whose supply chain PMS utilizes Six Sigma methodology,[35] which is the latest data-enabled, metrics-driven practice for performance improvement.[76,77] The firm's PMS takes advantage of DMC (e.g., ERP, data warehouses, RFID), dashboards of supply chain metrics for low/middle-level managers, and scoreboards for senior management.

Overall, a firm's SPC involves capability for observing, orienting, and deciding.[34] A key enabler of the capability for observing is supply chain metrics or KPIs, which are closely linked to the aforementioned four supply chain processes (P, S, M, and D). For example, benchmarking a firm's D process would require metrics such as on-time shipment, on-time delivery, perfect order fulfillment, and in-stock availability. These metrics are necessary measures for any firm's D process performance.

When developing SCM KPIs, companies should be aware of their business strategy and where their competitive advantage lies. The SCM KPIs need to be aligned with business strategy and competitive advantage. This can be accomplished by first identifying strategic aims, and then selecting the metrics that best identify how well the organization is accomplishing these aims. Balanced scorecards have been demonstrated as effective tools for performance measurement in supply chains.[78]

The capability for orienting visualizes supply metrics using technology-based dashboards/scoreboards, which helps firms understand the performance of supply chain processes. This requires good DMC. For example, OTD (On-Time-Delivery), which is the primary KPI measuring firms' delivery or D process performance needs two sets of data: the estimated arrival time (EAT) and the actual arrival time (AAT). EAT is usually available through ERP. Ascertaining AAT information requires inputs from third party logistics companies, original equipment manufacturers (OEM) or retailers (e.g., Best Buy).[31]

Through this process, all sources of data (e.g., customer, manufacturing, delivery) are determined, usually including internal legacy systems, third-party systems (e.g., logistics), and other external systems (e.g., retailers, suppliers, distributors). At this stage data extraction, transformation, and loading (ETL) are necessary to pull the data from various sources before data analysis and visualization,[17,20] which indicates the importance of DMC for performance management capability.

Finally, the capability for deciding occurs at the individual decision maker and/or organizational level. In both cases, the capability of deciding is associated with the use of data visualization and prescriptive analytics (e.g., simulation, what-if analysis, times series models). These analytical techniques and tools help decision makers determine probable causes of the performance issues with any area of supply chain processes and take actions to remedy the situation. The analytics-based performance management capacity thus includes analytic tools such as statistics and simulation, visualization tools to alert of potential problems through KPI, and other measures of key activities.

4. An Illustration: SCA in Action

The previous section presented a dynamic-capabilities view of BA for supply chain by discussing DMC, APC, and SPC. In practice, these capabilities are interrelated with each other. For example, DMC is critical for the use of analytical IT for supply chain processes and performance management. This section illustrates how they can be actualized in practice.

This illustration uses S&OP, which is an innovative supply chain practice to improve firm performance.[79–82] Top SCM companies have implemented S&OP successfully.[83–85] S&OP, as a coordination mechanism for SCM synchronization, involves people from diverse functional departments (marketing, manufacturing, procurement, R&D, finance, etc.) along senior executives. S&OP involves several steps or processes in developing a weekly or monthly SCM plan that synchronizes the demand plan, production plan, procurement plan, and shipment plan.[81] Anecdotal evidence shows that top performing firms have integrated BA into S&OP.[11,83]

Step 1: The first step involves the analysis of actual performance versus the plan developed in a previous week or month. This analysis identifies the discrepancies between Plan (e.g., sales, source, production, delivery) and Actual (e.g., sales, source, production, delivery). This cannot be accomplished without well-developed SPC. SC metrics and the visualization of such metrics using dashboards/scoreboards, make the analysis of SC performance in the past week or month possible. This allows fact-based discussion and decision making.[22,86]

Step 2: The next step reviews major events and trends. The relevant departments report any significant events. For example, R&D shares its progress in new product developments. The marketing department presents sales trends and competitive intelligence. The procurement department shares issues with suppliers and material requirements. This information sharing requires an effective handling of various types of data (e.g., product development, customer opinion, product release, market trends) from different data sources. DMC is the key in this process. In addition, analytics using descriptive statistics and times series analysis can help identify abnormalities in such processes as manufacturing, procurement, and delivery. Also, advanced analytics (e.g., web mining) are used for competitive intelligence, informing market trends and also acquiring customer opinions.[87] Thus, supply chain performance management capability is also deployed in this step.

Step 3: The following step involves demand analysis. The marketing or other relevant department(s) shares short term (8 to 16 weeks) demand information (forecasts and orders). This information is based on consensus forecasts, which are developed through layers of forecasting (individual sales people → regional office or branch → product-level aggregated forecast). Analytics such as "business assumptions package" (BAP)[81] offer the information about product offerings (new product release, end-of-life products, prices, promotions), market environments (competitive intelligence), and demand-related metrics (e.g., forecasting accuracy, forecasting volatility). DMC and performance management capability need to be well coordinated for successful demand analysis.

Step 4: Then, supply analysis follows demand analysis. The production and procurement departments offer a preliminary plan for production and procurement, which is based on demand plan and capacity constraints. The use of analytical IT resources embedding prescriptive (e.g., optimization modeling) and predictive analytics is becoming mandatory for complex supply analysis. For example, APS systems are used to support "the material flow across a supply chain and related business functions: procurement, production, transport and distribution as well as sales" (see Ref. 65, p. 579). The management, using optimization algorithms and simulation, can focus on supporting material and production planning. Thus, APC is the key in this step.

Step 5: Finally, S&OP increasingly includes financial optimization. Management reviews the plan for demand, production, and procurement. The respective departments reach a consensus in light of financial and operational optimization. Changes are made to those preliminary demand, production, and procurement plans, and advanced analytics, such as scenario-based planning, real-time analysis of internal and external data, and dashboards with financial metrics (e.g., total cost of goods, working capital requirements), are used for financial optimization.[11] Thus, APC and DMC are particularly important in this step.

5. Discussion & Implications: Propositions

This paper has aimed to offer a perspective on SCA as IT-enabled dynamic capabilities leveraging data, IT, and fact-based management. Thus, SCA is formed by DMC, APC, and SPC. This section presents a set of propositions and discusses some implications from this dynamic-capabilities perspective.

Data is the foundation for analytics. In other words, data is the basis for APC and SPC. The literature supports the positive impact of DMC on process and performance capability.[21] In turn, DMC is expected to positively affect different dimensions (e.g., customer satisfaction, production efficiency) of supply chain performance. For example, the capability of data transformation through data warehousing[46] leads to better organizational performance.

Proposition 1. *The greater the level of DMC, the greater the supply chain performance of the firm.*

The SCM literature has long recognized the very significant role of effectively managing supply chain processes (plan, source, make, and deliver) for the success of SCM.[55] APC is the firm's analytical capability for planning, sourcing, making, and delivering. The use of analytical tools and models makes supply chain processes more effective than they would otherwise be, and thus can improve supply chain performance.

Proposition 2. *The greater the level of APC, the greater the supply chain performance of the firm.*

Organizations cannot survive without good feedback mechanisms. Supply chain performance management plays such a role in improving SCM effectiveness and efficiency.[31,88] SCM exemplar firms are known to be advanced in performance management. Thus, it is expected that analytics-based performance management capability positively affects supply chain. Figure 3 displays these propositions.

Proposition 3. *The greater the level of analytics-based supply chain performance management, the greater the supply chain performance of the firm.*

Despite the growing interest in the use of analytics for supply chain, there is a lack of theory-driven, practical framework. This paper has proposed a dynamic-capabilities perspective on SCA as IT-enabled, analytical dynamic capabilities composed of DMC, APC, and SPC. According to this perspective, SCA is a second-order construct of firms' multiple capabilities: DMC, APC, and SPC. Thus, from aggregating DMC, APC, and SPC, the level of SCA can be estimated. SCA is expected to be positively associated with supply chain performance.

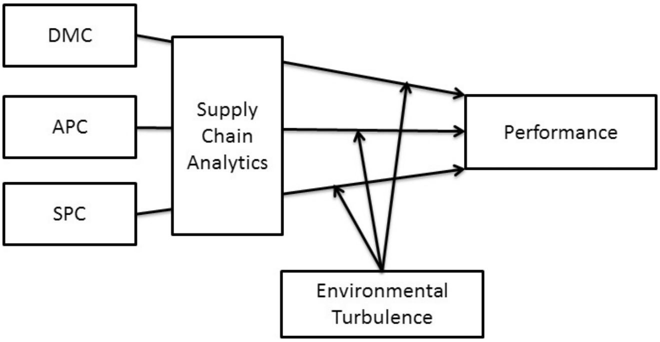

Fig. 3. Propositions.

Proposition 4. *The greater the level of SCA, the greater the supply chain performance of the firm.*

Finally, dynamic capabilities are critically important in fast-changing environments.[12,15] and found to be effective.[15,38] Thus, SCA as dynamic capabilities is expected to be a more effective means of managing supply chain in turbulent environments than in stable environments. Firms in turbulent environments can benefit more from building SCA than those in stable environments.

Proposition 5. *The greater the level of environmental turbulence, the greater the contribution of SCA to the supply chain performance of the firm.*

6. Conclusion

Industry reports and publications indicate that there is an increasing interest in BA for supply chain, as well as an interest in the practical applications of these analytics. Yet, there is a lack of academic research that explains the role and use of BA for supply chain and its impact on organizational performance. This paper has proposed a framework of SCA to understand how analytics can support organizations. Drawing upon the dynamic-capabilities literature, this framework describes SCA as IT-enabled, analytical dynamic capabilities composed of DMC, APC, and SPC. Proper attention should be paid to these three dimensions of SCA and their contribution to the formation of firms' SCA capability and SCM performance in future research. It is necessary to invest in all three capabilities and take full advantage of data, analytical techniques, and fact-based management principles when putting such practices into action. This paper has offered detailed descriptions of these dimensions and illustrated the application of SCA using S&OP. In further discussing the implications of the proposed framework, finally, the paper has presented a set of propositions predicting the positive impact of SCA and its individual capability on SCM performance.

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