How to Use Big Data to Drive Your Supply Chain

Nada R. Sanders

Big data analytics has become an imperative for business leaders across every industry sector. Analytics applications that can deliver a competitive advantage appear all along the supply chain decision spectrum—from targeted location-based marketing to optimizing supply chain inventories to enabling supplier risk assessment. While many companies have used it to extract new insights and create new forms of value, other companies have yet to leverage big data to transform their supply chain operations. This article examines how leading companies use big data analytics to drive their supply chains and offers a framework for implementation based on lessons learned. (Keywords: Decision Making, Supply Chain, Technology)

Over the past few years "big data" has emerged as the new frontier of IT-enabled innovation and is a subject in the forefront of business, science, and society as a whole.[1] It is virtually impossible to open a publication without seeing some reference to big data, new analytics breakthroughs, and novel insights. A recent article even refers to data scientists as the "sexiest job of the 21st century."[2] While the academic and scientific sectors are looking to big data for unprecedented opportunities to better understand the world, businesses are looking for a technology-based competitive advantage. As a result, big data analytics has become an imperative for business leaders across every industry sector—from healthcare to manufacturing to aerospace.[3]

The ability to capture, store, aggregate, and analyze data—and then extract intelligence—is now rapidly becoming a mandate for virtually all organizations. Leading-edge companies across the globe have reported benefits in their use of big data. Consider Walmart, eBay, Progressive Insurance, and Target.[4] These companies are succeeding in this game-changing environment by embracing and leading the change. They have used big data analytics to extract new insights and create new forms of value. After all, it is through big data that Walmart learned that customers prefer to stock up on the sugary treat Pop Tarts during a hurricane;[5] eBay identified which web designs generate the highest sales;[6] Progressive

Nada R. Sanders is the Distinguished Professor of Supply Chain Management at the D'Amore-McKim School of Business at Northeastern University. <n.sanders@neu.edu>

Insurance learned how to optimize insurance premiums by risk category,[7] and Target learned how to identify a pregnant customer.[8]

Analytics applications that can deliver a competitive advantage appear all along the supply chain decision spectrum—from targeted location-based marketing to optimizing supply chain inventories to enabling robust supplier risk assessment. Supply chains generate huge amounts of data that companies can turn into intelligence through analytics, from POS, GPS, and RFID to social media feeds. Success stories of companies that have harnessed the power of big data analytics abound, such as Amazon and Walmart. However, most companies have yet to leverage big data analytics to transform their supply chain operations.[9] The vast majority of companies are not the Amazons and the Walmarts. For them, acquiring new technologies and software is costly with an unclear ROI. Many are awash in data but are unsure how to use it to drive their supply chains.[10] Furthermore, many are engaging in fragmented utilization or implementation rather than a systematic and coordinated effort. The results are unclear benefits, including lack of real insight and competitiveness. The truth is that except for a few large companies, particularly those that are information-rich such as Linkedin, Facebook, and Google, most are struggling with deciding what to do and how to proceed.[11]

In order to extract the lessons of how leading companies use big data analytics to drive their supply chains, we conducted a multistage study over a period of two years. We first conducted exploratory interviews with executives and managers across a wide range of industries to identify critical challenges.[12] This was followed by a survey of senior managers and executives to identify specific implementation strategies and barriers.[13] Finally, we conducted in-depth case studies of four leading organizations that have successfully implemented big data analytics. Collectively, this process served to create an understanding as to the extent of use of big data across a wide range of organizations and identify common barriers to implementation. Further, we learned how leading companies use big data, commonalities of successful implementation, and strategies for overcoming barriers.

Our research resulted in three key findings. First, we present a prescriptive framework showing how companies can implement big data analytics to drive supply chains. Through the use of case studies and interviews the framework identifies hurdles of implementation and shows how exemplar companies do this. Analytics driven companies—Amazon, Walmart, Dell, and UPS—do all these things in a coordinated way as part of an overarching strategy championed by top leadership and pushed down to decision makers at every level. Although deep analytics capabilities are being developed for sub-functions along the supply chain, and are receiving much hype, they are often hyper-specialized. Unless the insights offered by these functional applications can be linked to the rest of the supply chain, their output may not provide tangible benefits. Second, we present stages of implementation through a maturity map. Proceeding through these stages ensures data quality, refinement of key metrics, and timely access to information by decision makers. We caution against following the hype and jumping into large-scale implementation without proceeding through the stages, given the need for organizational learning and continuous improvement. Third, we identify key issues companies should consider in outsourcing analytics. Big data analytics applications increasingly require deep technical knowledge that is not the core competency of most companies and we identify considerations in outsourcing this capability.

What is Different?

Big data without analytics is just a massive amount of data. Analytics without big data are simply mathematical and statistical tools and applications. Many of these tools have been around for decades, such as correlation and regression analysis. It is the combination of big data and analytics, fueled by today's computing power, which creates the ability to extract meaningful insights and turn information into intelligence. As Google's director of research, Peter Norvig, noted: "We don't have better algorithms. We just have more data."[14] However, this is only partially true. Actually, the availability of big data and the advancements in machine intelligence have created significant new opportunities for both the data and the development of algorithms. Based on an extensive review of scholarly research we identify what is different today.[15]

The first difference is the unprecedented *opportunity for inquiry*. The rapid pace at which all types of transactions, both economic and social, are moving online has enabled real-time digital capture of data. Certainly the notion of using analytical techniques to derive insights from data is as old as the field of statistics. However, the ability to capture and understand the content of human dialogue has expanded the types of data sets that can be analyzed. Large and complex data sets related to any type of phenomenon researchers want to study are now readily available. This can range from deconstructing the human genome to learning how the Internet affects financial markets[16] to learning how to optimize the timing of push-notifications to targeted customers with mobile analytics.[17]

The second difference is that the *nature of inquiry* has changed. In the past, data was collected with the aim of testing a human-generated hypothesis. Today, data are being collected for the possibility of testing hypotheses that have not yet been conceived and many of which are generated via computer. Machines are becoming smarter through self-teaching algorithms, continuously being fed data on a large scale. As such, the algorithm is able to detect every type of relationship between the variables, such as behaviors and demographics, asking interesting questions and refining them without active human intervention. As a result, the computer has now become an active participant in the inquiry process and is becoming capable of creating new knowledge and making discoveries on its own.[18] In medicine, for example, we are seeing computer learning used to identify unknown genes from prior knowledge of gene functions.[19] A large body of this research is being devoted solely to developing deep technical capabilities for machine learning.[20]

The third difference is that the *nature of experimentation* has changed. The Internet has created the ability to conduct large-scale experiments on many economic and social phenomena. One example is the ability of LinkedIn to turn granular structured and unstructured data into a quantification of member attitudes just by observing texts.[21] The company uses a home grown tool to "listen" to what members are talking about and is able to quantify the full range of member reactions including "pain points" and "moments of delights," enabling LinkedIn to turn data into insights. Similarly, Facebook researchers conducted a massive study determining that they could manipulate the mood of users.[22] These are essentially controlled experiments conducted on large numbers of people enabling the understanding of an unprecedented number of variables. Certainly there are privacy and ethical questions with conducting these experiments. However, the bigger point is that the ability for massive experimentation has changed the manner in which it can be conducted and the insights that can be gained.

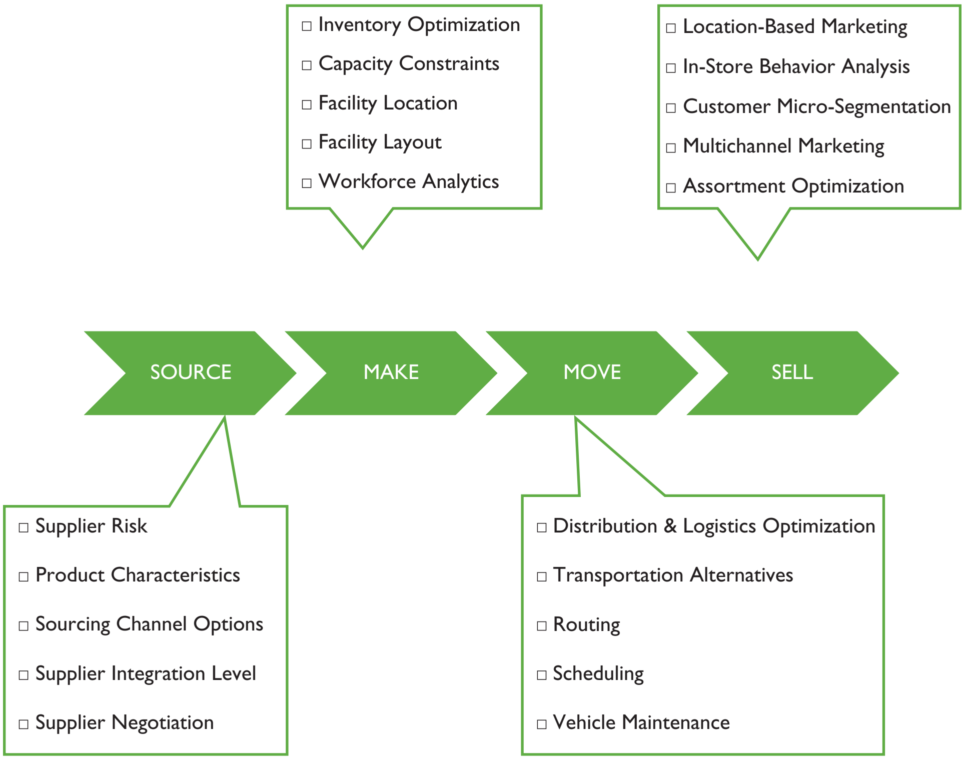
These three distinct differences of big data analytics point to it being one of the most significant "tech" disruptions in history. Big data is unique because of the volume, variety, and velocity of the data, which today is widely available and much less expensive to access and store.[23] However, our analysis of big data research developments shows that the majority of these advancements are highly functionally specific. A recent study identified five areas as having a "big impact" for big data research.[24] They are: e-commerce and market intelligence; e-government and politics; science and technology; health and medicine; and security and public safety. Of these, market intelligence is the only area directly related to supply chain management. Further, while providing deep insights, these analytics applications are highly fragmented. This fragmented nature of application development and inquiry leaves little opportunity for systematic implementation. This may be less problematic in other fields such as medicine where, for example, analytics can be used to answer targeted questions such as identifying hospital readmission for patients with congestive heart failure. However, it creates special challenges for executives who seek to improve entire organizational systems rather than merely one function.

Supply Chain Analytics Applications

Analytics applications are available along the entire supply chain spectrum—from source to sell (Exhibit 1). The largest growth has been seen on the marketing side, with applications constantly evolving to gain better market intelligence. Logistics has used analytics applications for routing and vehicle scheduling for years, while operations has been using applications that optimize operational requirements, from inventory and capacity to labor scheduling. Although lagging behind marketing, applications for both logistics and operations are increasingly growing in complexity and detail, with next generation algorithms adding unprecedented capabilities. Lastly, sourcing is increasingly seeing applications that segment suppliers, measure risk, and inform supplier negotiations. Although sourcing has lagged in application development compared to marketing and other supply chain functions it is forecasted to experience the largest growth over the next few years.[25]

These analytics applications offer deep insights and tend to be functionally specific. An example is a new capability from GE that provides enhanced asset reliability for clients by optimizing asset inspection, maintenance, and repair.[26] Typical

EXHIBIT 1. Analytics Applications Across the Supply Chain



of these applications the knowledge and insights provided are deep and the focus hyper-specialized.

Marketing Applications

Marketing analytics applications are customer oriented and are on the sell side of the supply chain. The nature of marketing has driven the development of big data applications that focus on capturing customer demand, enabling micro-segmentation, and predicting consumer behavior. In fact, micro-segmentation has become a highly important application of big data analytics. Although market segmentation has long been a marketing capability, the coupling of big data with sophisticated analytic tools has enabled micro-segmentation at increasingly granular levels.[27] Companies can now use technology to gather and track data on the behavior of individual customers, and then combine these with traditional market research tools to gain greater insight. The collected data is increasingly tracked in real time, enabling companies to quickly readjust their customer strategies. This is seen with retailers such as Neiman Marcus where behavioral segmentation is matched with a multi-tier membership rewards program.[28] The company uses sophisticated analytics to identify key customers and then creates targeted purchase incentives resulting in higher margin purchases from the company's higher-margin customers.

Another important marketing application is in price optimization.[29] Price optimization has moved to a new level, permitting analysis at a high granularity of data on pricing and sales. Pricing decisions can now be made in near real time using a variety of data sources, examples of which have become common in hospitality. Marriott International, for example, uses a sophisticated analytics system to optimize prices for guest rooms considering variables such as customer type and even the weather.[30]

Marketing applications are not restricted to traditional business-to-consumer (B2C) relationships. Although B2B offers special complexities, such as fewer customers characterized by infrequent but large orders, algorithms have been developed to track, segment, and better understand the spend of business customers. Further, these applications are becoming ever more sophisticated, such as providing “affinity analysis” that identifies which products a business customer is willing to buy from the company rather than its competitors.

Logistics Applications

Logistics applications help move goods through the supply chain and are some of the oldest. They have been used for optimizing inventory, identifying optimal distribution center locations and supply routes, and minimizing transportation costs. One highly utilized application is in transportation and routing. GPS-enabled big data telematics and route optimization are being used to optimize transportation.[31] Further, analytics applications can improve productivity by optimizing fuel efficiency, preventive maintenance, driver behavior, and vehicle routing. Tracking of disruptive events, such as weather, can be continually updated and routes re-optimized in real time. An example is UPS, which started gathering such data more than 20 years ago. The company uses an analytics tool called ORION (On-Road Integrated Optimization and Navigation) that enables drivers to find the most efficient route in their delivery areas.[32]

Applications can provide granular information such as segmenting transportation routes and including transit factors for different types of products.[33] An excellent example is in inventory management where RFID technology has been useful in tracking inventory in motion, capturing both location and quantity, as well as monitoring security. The technology is particularly important in the “cold-chain” where it is used to track ambient temperature and transit duration. These are especially important when transporting perishable items where the algorithms optimize order quantities as well as service levels with transit times, and can create alerts as soon as a problem is detected.

Operations Applications

Analytics applications are used in operations for a range of decisions—from inventory management and optimization of stock levels, to maintenance optimization and facility location. Measuring productivity and quality are finding large applications where companies can now run daily analyses of performance.[34] These statistics can be aggregated and reported on a more granular level, such as by store sales, SKU sales, and sales per employee. Although such applications have been available for years, what is now different is scale. These systems are moving ever closer to real time where they can alert companies of problems, including real-time changes in productivity or quality. Current applications enable granular reporting of statistics at high frequency, allowing managers to make more targeted real-time adjustments.

Workforce analytics has become an especially important area in operations.[35] Current technologies can reduce costs while maintaining service levels by optimizing labor, automating and tracking attendance, and improving labor scheduling. Retailers can analyze cashier performance at granular levels such as transactions per hour. At call centers, managers can analyze quality of customer service based on customer complaints, satisfaction surveys, or the percentage of customer issues solved with a single call. Analytics can also optimize staffing needs by matching forecasts with labor optimization, which is especially beneficial during peak demand periods.

Sourcing Applications

Analytics applications are becoming increasingly important in sourcing and are the fastest growing. Consider that in most manufacturing organizations sourcing represents the largest single category of spend for the company, ranging from 50 to 90 percent of revenue.[36] Therefore applying analytics here can yield great savings. A number of companies report using analytics to optimize sourcing channel options and integrate suppliers into their own operations. Some applications segment suppliers based on key characteristics, helping with sourcing strategy and balancing cost versus risk. Amazon, for example, uses analytics to determine the optimal sourcing strategy and manage all the logistics to get a product from manufacturer to customer. Analytics are used to determine the right mix of joint replenishment, coordinated replenishment, and single sourcing. In fact, Amazon applies advanced analytics across its fulfillment, capacity expansion, inventory management, procurement, and logistics functions in order to coordinate all supply chain management processes.[37]

Analytics can also be used to support supplier negotiations by providing a thorough analysis of customer preferences and buying behaviors. This information can be used to inform negotiations with suppliers by providing factual leverage. For example, companies can use information on prices and transactions to negotiate concessions on key products. Lastly, analytics is being used for tail-end spend, automating the process of managing this category as companies increasingly recognize its sizable monetary value.

Linking Applications Across Functions

These state-of-the art analytics applications exemplify the three distinct differences of today's big data analytics capability. We see an unprecedented opportunity for inquiry (e.g., consider that many retailers use facial-recognition cameras hidden in the eyes of mannequins to track shoppers, learn their behaviors, and increase sales, such as a "surveillance system" being utilized by Walmart, called Shopperception[38]); a change in the nature of inquiry (e.g., Tesco uses a self-learning Bayesian system for use in its online business called Tesco Direct that recommends particular grocery items customers may want); and a change in the nature of experimentation (e.g., retailers are using sentiment analysis to gauge the real-time response to marketing campaigns and adjust business course accordingly; both Starbucks and the Gap changed their logos using sentiment analysis in response to social media in real time[39]). This array of application capability is vast and even overwhelming. The insights they provide are deep, highly specific, and often hyper-specialized. Our case studies show that although leading companies rely heavily on these applications, they use them to drive their supply chains in a functionally linked manner as part of a coordinated overarching strategy. They do not select applications to optimize single functions or single decision areas in isolation. This is an important distinction.

One example of how analytics applications link the supply chain is illustrated by Walmart. Walmart is a leader among supply chain analytics competitors. Indeed its success as the world's largest retailer is at least in part based on the state-of-the-art analytics applications the company uses. These applications are used to link functions and coordinate its entire global supply network. The company collects more than 1 million customer transactions every hour,[40] all of which goes into a single integrated technology platform.[41] Sophisticated analytics is applied to this massive database and used across the supply chain. The collected information is then analyzed and used by managers to support every type of supply chain decision. At the store level, managers use the system to analyze detailed sales data and optimize product assortment. The system also enables inclusion of qualitative factors that help tailor assortments to local preferences. This ensures that customers have the products they want, when and where they want them.

Using analytics, the company has learned a great deal about customer preferences, some of it novel and surprising. For example, they learned that before a hurricane consumers stock up on food items that don't require cooking or refrigeration. A case in point is the algorithm uncovering that consumers purchase Kellogg's Pop Tarts, particularly strawberry Pop Tarts, before a hurricane. We can only assume that Walmart can then work with Kellogg's to stock shipments at stores in preparation for a hurricane. This detailed level of customer tracking gives Walmart deep insights into customer preferences and buying behavior. Armed with this type of factual knowledge also enables Walmart to win pricing and distribution concessions from its suppliers.

Walmart's analytics and data availability extends to all its suppliers, currently numbering more than 17,400 suppliers in 80 countries. These suppliers are required to use the company's analytical platform that gives the suppliers a view of in-store demand. This is Walmart's "Retail Link" system that can be used to track the movement of all products. Using the system, suppliers know in real-time when stores need to be restocked rather than waiting for an order from Walmart. The system allows suppliers to search for information on sales, shipments, purchase orders, invoices, claims, and forecasts, and it allows them to run data queries. The system also gives suppliers access to Walmart's assortment planning, enabling suppliers to create store specific modular layouts based on sales data and store traits.

Our case studies show that leading companies like Walmart understand that optimizing one supply chain function is insufficient. Walmart uses big data analytics to link the entire chain from source to sell. Its applications on the sell side capture and track demand through POS data. This information moves efficiently through the supply chain to inform all the other supply chain functions, coordinating POS data with inventory information from RFID sensors. This is the role of the Retail Link platform that serves to connect and coordinate the entire supply chain, matching supply with demand. Information at any one point in the supply chain—say, a shortage in supply, delayed shipments in transportation, or production stoppage in operations—is conveyed to all other supply chain functions informing them and coordinating action. By making supply and demand signals visible between retail stores and suppliers, the company optimizes all its supply chain decisions—from customer fulfillment to inventory tracking to automatic purchase orders through its supplier portal.

Another example is Zara, the major division of the Spanish retailer Inditex. Zara is a global leader in "fast fashion," an industry characterized by the ability to generate quick turnover of merchandise at affordable prices. Low prices coupled with freshness of assortment are requirements. Success mandates rapid information access and quick supply chain response,[42] dependent upon a data-driven coordinated supply chain. The first hallmark is Quick Response, a set of standards for information exchange and supply chain management, enabling significant reductions in lead times and efficiency due to rapid information exchange. This includes real-time information on item sales, stocking levels, and inventory movements that are then quickly used to modify production, distribution, and procurement decisions. This information is also used to create dynamic assortment, which are frequent assortment changes that can occur monthly, weekly, or even daily and that appeal to high-fashion customers. The result is low inventory coupled with high responsiveness. To further enhance these capabilities Zara recently implemented an RFID system to track items from factory to point of sale, getting a real-time picture of which fashions are selling, prompting an instant order to the stockroom each time a garment is sold, and keeping track of all this data.[43] Like Walmart, the data and analytics are shared across functions and the supply chain in real time. However, in Zara's case, this coordination is made easier as Zara is vertically integrated, owning its stores and managing its own assortments.

Yet another example is Seven-Eleven Japan, the largest convenience store network in the world. With a professional customer base, the company experiences demands similar to those seen in fast fashion, such as constantly changing customer preferences and last minute customer orders for prepared items. The company has a strategy with a focus on freshness, and its Just-in-Time supply chain relies on a sophisticated information system that gathers point-of-sale data shared with suppliers and distributors.[44] The data is also used to forecast future trends and, like Walmart and Zara, mined to optimize assortments. By analyzing hourly sales trends for individual items, the company optimizes delivery schedules and minimizes waste. Based on data analysis it even changes individual product assortments, such as that of milk products rearranged a few times a day to better suit customers' evolving needs. One assortment is small containers of milk in the morning for workers to pick up on way to work. By midday, the assortment is changed with lunch-sized servings offered for students. At the end of the day, larger cartons are placed for parents bringing milk home in the evening. Every aspect of such assortments—timing, volume, display, and deliveries—is optimized based on data and coordination with suppliers.[45]

These examples show that leading companies use state-of-the art analytics applications to not only gather data and local intelligence, but to connect the supply chain. These companies understand that the supply chain is a system and, as such, functions need to be linked and coordinated for the system to work. Optimizing costs along one function typically results in increased costs in another. Marketing, for example, may use analytics applications to customize product offerings. However, if operations are not able to produce the desired product versions and quantities, or if logistics is not prepared to deliver them, the system will underperform.

Implementation Hurdles

Our survey of senior executives and managers finds that the majority (seventy-eight percent) believe that big data analytics is a technological priority for the future. Sixty-eight percent expect to be making some degree of supply chain technological software investment in the coming year. However, eighty-three percent expressed substantial concerns regarding costs of the technology and the adoption decision for their individual needs, considering costs versus capabilities needed. Sixty-eight percent stated they were awash in data and seventy-two percent engaged in fragmented implementation efforts.

Based on our findings, we identify four hurdles that prevent companies from taking advantage of the big data revolution.

- *Needle in a Haystack*—Many companies are feeling the need to rush and implement analytics applications to keep up with the hype. As a result, they are often using analytics randomly in search for causation and relationships with the hope that something will eventually turn up. Rather than being focused, analysts are in many cases engaging in mere number crunching, often uncovering relationships that are false positives resulting in wasted time and money. An executive at a financial services firm described a scenario where the company's analysts are "number crunching" through huge amounts of data in the hope of identifying ways to improve forecasts. The problem, as he put it, is that "we are just running random experiments to see if anything will show up." As commented in a recent *Harvard Business Review* article, "a pure data mining approach often leads to an endless search for what the data really say."[46]
- *Islands of Excellence*—Often companies select applications designed for a specific process. Although the algorithm may optimize that process and be very efficient, there may be little bearing on optimizing the supply chain if the process isn't linked across the supply chain. An executive at a mid-sized company described his company's effort to optimize transportation fuel costs without linking it to other variables such as lost sales and prioritization of deliveries. Another interviewed analyst proudly exclaimed: "I have an algorithm to optimize the content of our kitchen cabinets!"
- *Measurement Minutiae*—Many companies find that they have too many metrics. This is the hallmark of Measurement Minutiae, which is trying to measure everything. Few companies have the diligence to actively manage all of the metrics they have created and most of the companies don't know which

ones to focus on. An executive at a large shelf-stable food company told us: "We have over one hundred different metrics. My primary job is to drastically cut this number so we know what matters." Many of the companies we interviewed were settling on easier to measure metrics, such as margins, revenues, and inventory turns, resulting in metric proliferation. By contrast, a few companies had taken the time to develop a smaller number of customized metrics that actually measured relevant performance.

- *Analysis Paralysis*—Many companies are overwhelmed with the rapid change of technological capability. They understand they must do something but are in a state of paralysis. Many indicate they are drowning in data—gathered from POS systems, websites, internal transaction processes, and social media. For most, it is difficult to digest all of the data, technology, and analytics that are available to them. Many indicate that they cannot absorb the new analytics technologies being made available to them. As a result, they find that they are in a state of paralysis. In our interview, a CPG executive exclaimed: "We have so much data but have no idea how to use it! What do we do with all this data? Where do we begin?" This was a common sentiment frequently stated.

Coordination Imperative

Indeed, companies leading in big data analytics are "number-crunchers" with superior technology. However, not all have the latest analytics applications. Our study finds that these leading companies do much more than just acquire technology. They have the right *focus* so that the acquired applications are not random but directly support the value proposition of the business. To drive entire supply chains, their efforts are *coordinated* across all supply chain levels.

Analytics efforts are resource intensive. As a result, companies must choose where to direct these efforts. It is not possible to effectively focus on everything. Big data implementation efforts that tackle too many areas can easily become diffused. This can lead companies to lose sight of the business purpose behind the effort. We find that successful implementation requires companies to focus their big data efforts by strategically selecting areas or initiatives that support their overarching strategy. A good example is UPS, which had initially focused their analytics efforts on improving logistics operations.[47] Since then the company has expanded analytics efforts to provide superior customer service. Further, internal analytics efforts must be coordinated with customers and suppliers. Recall that Walmart requires its suppliers to use its Retail Link system to monitor product movement by store, to plan promotions and layouts within stores, and to reduce stock-outs. Procter & Gamble has a similar platform called Joint Value Creation. It allows data analysis for both its retail customers and suppliers and helps improve responsiveness and reduce costs.[48]

Coca-Cola provides another example of a big data driven, end-to-end supply chain. Analytics applications are used along all supply chain functions that "talk" to one another to ensure coordination of activity. First, an algorithm is used to engineer the taste of its orange juice. Next, a computer model is used to direct everything from picking schedules of oranges to the blending of ingredients needed to maintain a consistent taste. The company has spent $114 million to expand its U.S. juice bottling plant, which is completely technology driven and claims to be the largest in the world. At this plant, the company uses a computer algorithm it calls Black Box, which can be viewed as a "secret recipe." Black Box contains granular data from more than 600 flavors that make up what customers perceive as an "orange taste." The algorithm then matches this data to the taste of each batch of raw juice. The profile of each batch specifies acidity, sweetness, and other taste attributes. The algorithm then blends batches of raw juice to replicate the taste and consistency perceived as "orange," including the amount of pulp added. Further, the algorithm is tied to satellite images of fruit groves to ensure the fruit is picked at the optimal time for Coca-Cola's bottling plants. To generate the computations, the algorithm also considers external factor such as crop yield, current prices, and weather patterns. Every aspect of the supply chain is optimized and standardized, but can be quickly updated. In fact, the mathematical model can quickly create new plans—in a matter of five or ten minutes—with any new information. Jim Horrisberger, Director of Procurement, put it this way: "You take Mother Nature and standardize it."[49]

The Framework

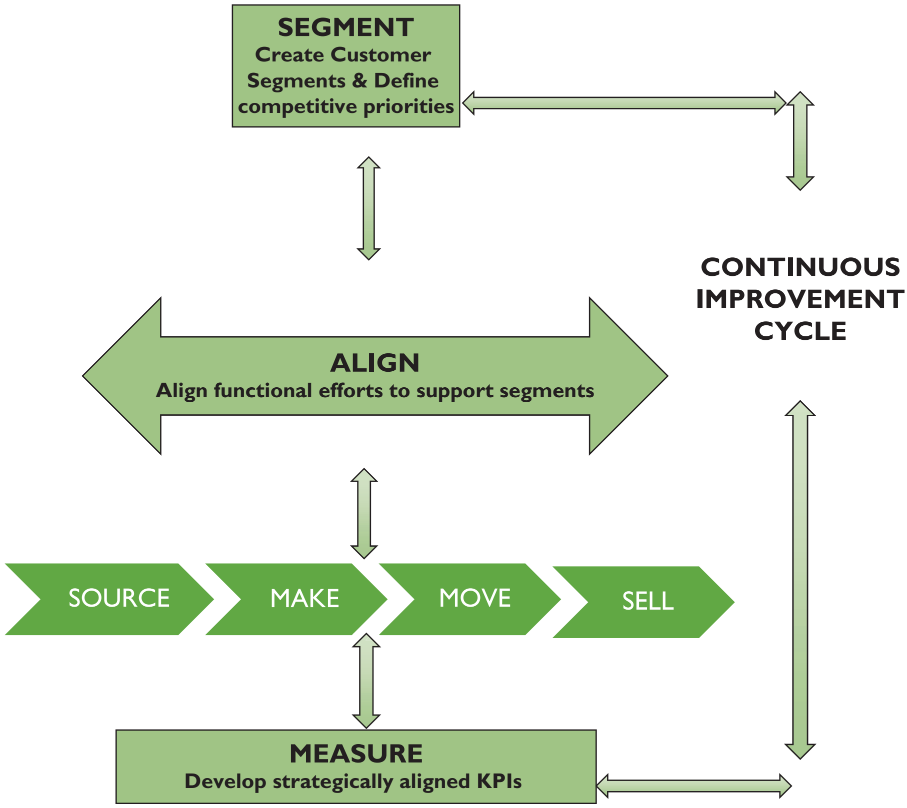
Clearly big data analytics has a transformative potential for supply chain management. However, based on our case studies we find that companies who have actually achieved this have three things in common. First, their efforts are driven to support the company's strategy rather than random efforts of exploration. Second, these companies use applications along all supply chain functions in a coordinated manner rather than optimizing just one function. Third, they measure performance through carefully selected metrics and use these for continuous improvement, further guiding their analytics efforts. Based on this, we have developed the framework shown in Exhibit 2.

Segment

The first step in the framework is to use analytics to create optimal supply chain segments with clear attributes. This defines exactly how the company intends to compete in each segment and helps establish the needed focus. It helps companies avoid the hurdle of *needle in a haystack* or creating *islands of excellence*. Indeed, companies have been segmenting customers for decades by attributes such as demographics, purchase patterns, shopping attitudes, and behavior. These segments have different product and customer service requirements, and they are served through different channels and different supply chains.

Almost twenty years ago, a seminal article described the then technological capability and asked: "Why haven't the new ideas and technologies led to improved performance?"[50] It went on to explain that the nature of product demand requires different supply chains and suggested dividing products into "functional" (e.g., stable product demands with long life cycles) and "innovative" (e.g., uncertain product demand with short life cycles and great variety), each having different supply chain structures. The underlying premise still holds true. However, today's analytics enables data scalability with granular data being aggregated in an infinite

EXHIBIT 2. Framework for Implementation



array of possibilities, making it possible to optimize segment categories in new and novel ways, well beyond a binary set.

A critical part of creating segments is defining competitive priorities in each segment, which specify how a company intends to compete in each segment. Defining unique segments and their characteristics leads to a clear identification of competitive priorities for each segment. These should be specific and may include target levels for customer service, cost competition, quality, time, or responsiveness. Each of these competitive priorities translates into different operational requirements.[51] This results in different supply chain structures, different suppliers, transportation and operational strategies, and thresholds of performance for each segment. Consider that supply chain segments that focus on cost have very different supplier requirements than those that compete on innovation, quality, or customer service.

Each segment focuses on different objectives. The goal is to develop segments that optimize customer needs and supply chain requirements to serve each segment. Analytics algorithms can then be selected to optimize decision processes to support the competitive priorities in each segment—such as optimizing customer service while keeping a threshold on costs. An excellent example is the apparel retailer American Eagle Outfitters. The company used analytics to create clusters of its more than 750 stores based on the types of assortments to which shoppers were most responsive.[52] They were then able to identify that customers in Western Florida bought merchandise similar to those in parts of Texas and California. This segmentation enabled the company to better target store assortments and better control pricing in each segment.[53]

Align

The next step in the framework is to align organizational functions so that their efforts support segment attributes and competitive priorities. Aligning means integrating processes across the supply chain. As a result, each supply chain function applies its analytics efforts to support the stated competitive priority, rather than engaging in random exploratory efforts. Alignment integrates the organization and its supply chain horizontally. This is accomplished through the sharing of intelligence across functions and supply chain partners, and engaging in joint decision making, such as Sales & Operations Planning (S&OP). This is precisely what was illustrated in the examples of Walmart, Zara, and Seven-Eleven Japan.

Alignment also avoids fragmented efforts. Staying true to alignment can be challenging given the endless array of new analytics applications and the hype surrounding them. However, functional alignment should drive application selection rather than analysts engaging in efforts that do not support competitive priorities. Without alignment, no amount of data mining will yield a system-wide competitive advantage.

One part of alignment is to use analytics to sync up supply and demand. Big data can be a huge source of aid in this process as it enables "demand sensing" and helps drive other supply chain decisions. An example is Ford, which uses big data analytics to align its supply chain. FordDirect is a platform that provides an interface for information sharing between the customer, dealer, and manufacturer in real-time. It can be used to customize vehicles, manage inventory, and handle customer service needs such as obtaining financing.[54] The platform enables sharing of information permitting supply chain coordination.

Measure

The third step in the framework is to measure performance. We find that leading companies develop strategically aligned KPIs to measure segment attributes. Here the analytics initiatives are measured with targeted and measurable KPIs that are routinely reviewed. The key is to identify the right metrics for the phenomena the company needs to optimize. This can be accomplished using strategically aligned KPIs agreed upon by all process members. These metrics should also measure degree of alignment, integration, and cross-enterprise cooperation. We find that a number of leading companies use analytics to look for new meaningful metrics that are driven by strategy, core competencies, and measure the value proposition of the business. Big data analytics enables and necessitates the development of new metrics that offer greater insight. An example of this type of innovation is seen the movie *Moneyball* where traditional baseball metrics to evaluate players, such as "batting average," were changed to new and more meaningful metrics, such as "on-base percentage."

Finally, a feedback loop should exist between metrics—monitored on a continuous basis—and the defined segments and their competitive priorities. The metrics should be used to refine the segmentation process and realign the competitive priorities. Through *kaizen*—continuous improvement—we have learned that the best and sustained change occurs from gradual improvements.[55] This should be an ongoing process. Big data algorithms can significantly assist with this, such as automatically tracking these metrics and creating alerts when deviations occur.

Implementation in Action

Our framework is prescriptive. It provides the steps companies should follow in implementation. Technology and big data analytics are merely tools in achieving a competitive advantage enabling better segmentation (Step 1), alignment that unifies functional areas (Step 2), and use of metrics that drive performance (Step 3). Lastly, the framework is cyclical following principles of continuous improvement. It should be routinely refined and realigned, such as part of the S&OP cycle (Step 4). Selection of analytics applications should follow and support decisions at each step.

Dell offers an example of this type of implementation. Only a few years ago, Dell competed on the configure-to-order model.[56] Here customers could order customized computer configurations on the company's website, including variations in models, software configurations, memory, screens, design, and every other customizable feature. This supported the company's strategy of customization. However, from an operations and supply chain standpoint it was a nightmare. The combinations of customer options resulted in over seven septillion[57] possible configurations of Dell products. Although the options were good for customers, the inventory implications were staggering.

Then the company moved to an analytics driven system that allowed it to maintain the same strategy but optimize inventory decisions. They still wanted to satisfy the diverse needs of a broad set of customers. However, they also wanted to keep costs as low as possible. To respond to the challenge the analytics team decided to use historical order data to run cluster analysis to determine the most common configurations customers were selecting. The finding was that there was actually a great deal of commonality in ordering. Analyzing the data, they were able to reduce the seven septillion options to just a few million. They were then able to segment their product configurations. They identified the models so common that they could stock these in preconfigured inventory. Coordinating with their supply chain partners, these common configurations could be built ahead of time with the lowest margins and stocked in inventory to be shipped. For this segment, next day delivery was made possible, providing high customer service with low inventory cost. This level of segmentation and analyses enabled Dell to sell precisely what the customer wants but produce and deliver it in a cost-effective manner. This new system has brought the company an additional $40 million in revenue. It also exemplifies the benefits of using big data analytics to segment markets and customers, and then use analytics for product configurations and coordination with supply chain partners.

Implementing Technological Capability

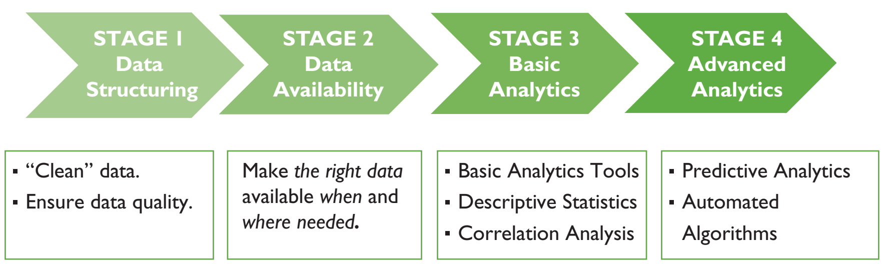
Our study of leading companies reveals a process for implementing analytics capability. There is no one big data solution. Instead it is a set of analytical tools available with varying degrees of complexity, cost, and capability. We have learned that not every company needs the most powerful analytics capabilities to be successful. Further, implementation of these capabilities is best accomplished through a gradual evolving process of maturity as discussed below. As a number of interviewed executives noted: “It is a journey.”

The Maturity Map

Most organizations follow an evolution in their implementation of analytics. They utilize efforts that build big data capabilities over time and learn through the process of continuous improvement. There are four stages of maturity in this evolution, which are presented as a maturity map in Exhibit 3. The first stage is digitizing and structuring the data, what we call “data structuring.” This is a process that ensures that the data generated are clean, structured, and organized in such a way that they can be used for further analysis. This involves a process called “scrubbing” the data to remove errors and ensure data quality. Our interviews with executives reveal a repeated concern with “dirty data.” Many quoted the adage of “garbage in and garbage out.” Companies are awash in data but much of it may not be reliable.

The second stage of evolution requires making the data available to all who need it when they need it. Available data can be a powerful driver of value by itself and is an important first step in integrating datasets to create more meaningful business insights. Further, data needs to be available in usable form to support decision making in the respective areas and functions. Making the right data, in the right form, available when and where it is needed is a significant process challenge.

EXHIBIT 3. Implementation Maturity Map



The third stage is applying basic analytics to the data. This covers a range of methodologies, such as basic data comparisons, correlations, and regression. Here, relatively standardized quantitative analyses are used, such as descriptive analytics. These do not require customized analyses designed by people with deep analytical skills as in the subsequent stage. In fact, many companies do not need the highest level of analytics to achieve huge gains. Many can gain success from this stage without investing in more advanced technologies. Correlations and simple regression alone can provide powerful insights. In fact, we found this to be particularly true for a few small and mid-sized companies which, given their scale, were able to more easily implement coordinated solutions that utilized basic analytics.

The fourth and highest level is applying advanced analytics, such as predictive analytics, automated algorithms, and real-time data analysis that can create radical new business insight. They allow new levels of experimentation to develop optimal approaches to targeting customers and operations, and to opening new big data opportunities with third parties. Leveraging big data at this level often requires the expertise of deep analytical talent.

As companies gain competency, they move along the maturity map. It is a mistake for companies to try to jump to the last stage of the maturity map without first going through the first three stages. Companies need to go through the organizational adaptation, learning, and continuous improvement needed to move through the stages. We find that when leading companies implement analytics, they move through the maturity map. They tend to begin on a small, targeted, and carefully selected pilot project. This is called a "process of purposeful experimentation." It can be the best path toward becoming an organization that fully leverages big data. It also enables learning. This is a very different and more effective approach than a complete plan for the enterprise prior to doing any implementation. It can begin by selecting a few high-potential areas in which to experiment with big data and then scaling upward. It is easier to create value from such small projects rather than jumping directly to complex analytics implementation. We found a few examples of the latter resulting in *islands of excellence*.

Kaiser Permanente offers an example of staged implementation.[58] The company began their big data efforts by concentrating on one IT project focused exclusively on patients with long-term conditions. Then they moved along the maturity map creating specific disease registries and panel management solutions, rather than an all-encompassing IT solution addressing a range of problems. This type of slow and targeted approach—particularly as it supports competitive priorities—is the best strategy.

Lastly, as companies move through the maturity map they need to concurrently build their IT infrastructure with security in mind. Many companies address security post hoc by layering new security on top of the existing architecture, which often results in greater security gaps.[59] Even the earliest stage of the maturity map should include security considerations. Although integrating analytics across the supply chain provides tremendous benefits, it unfortunately also creates a host of cybersecurity challenges and vulnerabilities against which companies need to guard.

Analytics Outsourcing

Successful use of big data analytics does not only depend on availability of data and analytical tools. It also depends on the ability of organizational members—leaders, managers, and employees—to be able to use them. This is a significant problem. Most companies lack the capabilities to do all the analytical work that is required. As technological capability advances, the gap between available technology and the ability to use it will continue to grow. Many companies need specialized software available from external vendors. They may also need access to additional databases. Further, they may need someone to orchestrate the use of all the technological elements. In our interviews we found outsourcing analytics and hiring an outside vendor to be a major concern for companies.

To quickly gain access to technological capabilities needed, many companies are turning to analytical outsourcing. In fact, analytical outsourcing is a rapidly growing trend. Leading companies outsource various aspects of their analytics capability, from Walmart outsourcing to Mu Sigma to Limited Brands and Pottery Barn working with Alliance Data.[60] The need for these services is obvious given the high level of skills required. As a result many providers, from software vendors to consultants, are now providing analytical assistance. External providers can offer access to data and software. They are on the technology frontier and can provide a breadth of analytical assistance. Further, many external providers specialize in certain industry segments, say healthcare or fast-fashion, and can quickly bridge the gap between the company's needs and technical knowledge.

Two key dimensions of outsourcing are the *scope* and *criticality* of the engagement.[61] Scope is the degree of responsibility outsourced, while criticality is the importance of the outsourced activities. The greater the scope of the outsourced task, the larger the relinquishing of control by the organization. Similarly, the greater the criticality of the outsourced task, the greater the consequences of poor performance. For example, the outsourcing engagement can be small in scope, involving just one aspect of analytics—such as purchasing data or conducting analysis on one existing data set. It may mean supplementing current staff with either onshore or offshore analytical consultants. On the other hand, it may mean outsourcing most of the company's analytics capabilities.

The potential benefits of outsourcing are large as they enable an organization to tap into highly specialized skills it currently does not have. However, outsourcing can create a range of risks and dependencies, not the least of which is the leaking of proprietary information and issues of data security.

Companies should be especially careful when outsourcing activities with large scope and criticality, where these risks can be particularly dire. Consider an example where some 108,000 Florida state employees had their personal information compromised when the outsourcing service provider improperly allowed subcontractors in India to index state personnel files.[62] Another example is that of Target where a data breach was tied to employees of a company that provided call center support service to Target National Bank, the issuer of the Target Visa Card.[63] These outsourcing engagements need to be monitored carefully.

Also, specifying liability for data breaches and adding specific data security requirements into contracts are becoming increasingly common.[64]

Our interviews revealed a wide variation in engagements. As a result, we suggest companies begin by first understanding their current capabilities, processes, and needs. Otherwise they may find that they have purchased capabilities that do not enhance the business value, are beyond their scope of understanding, or worse yet solidify bad processes (as we observed in a few cases). Second, companies should compare providers, beginning with those who offer analytics applications for their specific industry versus those who work across industries. Some companies, for example, preferred providers who had expertise in their specific niche, such as location applications in healthcare, while others specifically wanted applications successful in other industries. The idea here is that it may be possible to gain a competitive advantage by partnering with those outside of one's industry. IBM showcases the advantage of this by recently launching analytics solutions based on data collected from over 50,000 different client engagements across a wide range of industries, from oil and gas to healthcare to retail to banking. These analytics solutions cut across twelve different industries and are customized per industry segment yet standardized to serve as "out of the box" solutions with preset dashboards. The company could only achieve this capability given its large scale and industry breadth of best practices learned.[65] Third, selection of external providers should include their ability to seamlessly interface with systems currently in place. A number of companies we spoke with used multiple niche providers with the caveat that the systems were all able to communicate. Lastly, the ability to scale and go beyond the company's immediate need is a high priority. Some partners may build short-term technical capabilities, while others can help to build long-term organizational capabilities that are highly scalable. In fact, a few companies we interviewed ultimately chose to develop their own internal analytics capability after a careful analysis of options.

The need for outsourcing will grow as IT capabilities evolve requiring ever more specialized skills. As a result, companies need to develop a skillfully formulated analytics outsourcing strategy. This strategy must clearly delineate which analytical capabilities the company wants to build for itself, and which they will outsource from partners. It must also specify the long-term plan for building capabilities over time, in addition to meeting short-term goals.

Conclusion

Big data analytics is not just another technology. It is the nexus of software, computing, and technological capabilities that has ushered in an era of radically different competition and is a "tech" disruption of historic proportions. This study was motivated by the need to understand how big data drives leading supply chains and to identify the characteristics of successful implementation. Despite the hype, the majority of companies have yet to leverage big data for their supply chain operations, they are engaging in random implementation efforts, and many do not know how to proceed. Contributing to this are analytics capabilities that offer deep insights but are hyper-specialized. This creates special challenges for supply chain management where executives need to improve performance of entire organizational systems rather than mere functions.

We identified three distinct differences of today's big data analytics capability: unprecedented opportunity for inquiry, change in the nature of inquiry, and change in the nature of experimentation. This has led to an array of application capabilities that is vast, tempting, and even overwhelming. Thus it is more important than ever to look to practices of firms succeeding in this arena and identify their common strategies. We found a few key lessons from these companies. First, these companies use big data applications that are coordinated across supply chain functions matching supply with demand. They do not select applications to optimize single functions or single decision areas in isolation. Second, their efforts are focused and driven by strategy, resulting in targeted tactical applications rather than random efforts of exploration. Third, they rigorously measure performance using carefully developed metrics and engage in continuous improvement. Fourth, leading companies follow "a journey" in their implementation efforts, beginning with a carefully selected pilot project, rather than jumping into wide-scale adoption. These are important lessons that should guide the vast majority of companies that remain uncertain as how to proceed in this new analytics era full of opportunity.

Notes

1. Michael E. Porter and James E. Heppelmann, "How Smart Connected Products are Transforming Competition," *Harvard Business Review*, 92/11 (November 2014): 64-88; D. Barton and D. Court, "Making Advanced Analytics Work for You," *Harvard Business Review*, 90/10 (October, 2012): 79-83; H. Chen, R. Chiang, and V. Storey, "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly*, 36/4 (December 2012): 1165-1188; S. Baker, *The Numerati* (New York, NY: Houghton Mifflin, 2008).
2. T. Davenport and D. Patil, "Data Scientist: The Sexiest Job of the 21st Century," *Harvard Business Review*, 90/10 (October 2012): 70-76.
3. James Manyika, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, and Angela Hung Byers, "Big Data: The Next Frontier for Innovation, Competition, and Productivity," McKinsey Global Institute White Paper, May 2011.
4. Thomas H. Davenport and Jeanne G. Harris, *Competing on Analytics: The New Science of Winning* (Boston, MA: Harvard Business School Publishing, 2007).
5. "A Different Game," *The Economist*, February 27, 2010, pp. 6-8.
6. Thomas H. Davenport, "Realizing the Potential of Retail Analytics Plenty of Food for Those with the Appetite," *Working Knowledge Research Report*, Babson Executive Education, 2009, pp. 1-42.
7. Thomas H. Davenport, "Competing on Analytics," *Harvard Business Review*, 84/1 (January 2006): 98-107.
8. Kashmir Hill, "How Target Figured Out a Teen Girl Was Pregnant Before Her Father Did," *Forbes*, February 12, 2012.
9. Bill Schmarzo, "KPMG Survey: Firms Struggle with Big Data," *InFocus*, February 6, 2014, <https://infocus.emc.com/william_schmarzo/kpmg-survey-firms-struggle-with-big-data/>.
10. "The Promise and Challenge of Big Data," *A Harvard Business Review Insight Center Report*, September 2012.
11. P.B. Goes, "Big Data and IS Research," *MIS Quarterly*, 38/3 (September 2014): iii-viii.
12. Fifty-two open ended interviews were conducted from industries including pharma (12%), manufacturing (53%), healthcare (11%), retail (17%), hospitality (5%), and financial services (2%). Interviews were conducted in person following an interview protocol and conducted at the following annual professional conferences Council of Supply Chain Management Annual Conference (CSCMP), Supply Chain Leader's in Action Conference (SCLA), Institute for Supply

Management (ISM), and the INFORMS Analytics & Operations Research Conference (2014). Interviewees included eighteen senior executives and SVPs, twenty-one mid-level managers or directors, and thirteen senior analysts.

13. Survey of 300 companies with 102 respondents (response rate 34%) using Dillman's Survey Design Method (Dillman et al., 2009); respondents were high-level managers and executives from manufacturing (53%), retail (31%), and wholesale/distribution (16%); t-tests for differences in means between the initial and final quartiles of respondents was used for non-response bias (Armstrong and Overton, l977). D.A. Dillman, J.D. Smyth, and L.M. Christian, *Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method* (Hoboken, NJ: Wiley & Sons, 2009); J.S. Armstrong and T.S. Overton, "Estimating Nonresponse Bias in Mail Surveys," *Journal of Marketing Research*, 14 (1977): 396-402.
14. Andrew McAfee and Erik Brynjolfsson, "Big Data: The Management Revolution," *Harvard Business Review*, 90/10 (October 2012): 60-68.
15. Scholarly research on big data analytics is becoming extensive. Our major journals, such as *Management Science, MIS Quarterly, Production Operations Management, International Journal of Forecasting* and others, have commissioned special issues on these topics. A new journal called *Big Data* has been recently launched with thousands of recently downloaded articles.
16. X. Zhang and L. Zhang, "How Does the Internet Affect the Financial Market? An Equilibrium Model of Internet-Facilitated Feedback Trading," *MIS Quarterly*, 39/1 (2015): 17-38.
17. "Increasing User Engagement with Mobile Analytics," presented at INFORMS Conference on Analytics & Operations Research, April 12-15, 2015, Huntington Beach, CA.
18. V. Dhar, "Data Science and Prediction," *Communications of the ACM*, 56/12 (2013): 64-73.
19. Michael P.S. Brown, William Noble Grundy, David Lin, Nello Cristianini, Charles Walsh Sugnet, Terrence S. Furey, Manuel Ares, Jr., and David Haussler, "Knowledge-Based Analysis of Microarray Gene Expression Data by Using Support Vector Machines," *Proceedings of the National Academy of Sciences of the United States of America*, 97/1 (2000): 262-267.
20. One part of data science is focusing on "Deep Learning" using algorithms to extract high-level, complex abstractions as data representations through a hierarchical learning process. Progressively complex abstractions in the hierarchy are "learned" at a given level based on simpler abstractions from the preceding level. Deep Learning enables analysis and learning from big data that is unstructured. For a good representation see Maryam M. Najafabadi, Flavio Villanustre, Taghi M. Khoshgoftaar, Naeem Seliya, Randall Wald, and Edin Muharemagic, "Deep Learning Applications and Challenges in Big Data Analytics," *Journal of Big Data*, 2/1 (December 2015): 1-21.
21. "How LinkedIn Leverages Text Analytics to Hear Customer Voices in Today's Social Media," INFORMS Conference on Business Analytics & Operations Research, April 12-14, 2015, Huntington Beach, CA.
22. A.D.I. Kramaer, J.E. Buillory, and J.T. Hancock, "Experimental Evidence of Massive-Scale Emotional Contagion Through Social Networks," *Proceedings of the National Academy of Sciences of the United States of America*, 111/34 (2014): 8788-8790.
23. McAfee and Brynjolfsson, op. cit.
24. Chen, Chiang, and Storey, op. cit.; also discussed in Goes, op. cit.
25. "Gartner Predicts Business Intelligence and Analytics Will Remain Top Focus for CIOs Through 2017," December 16, 2013, <www.gartner.com/newsroom/id/2637615>.
26. William Ruh, Vice President of GE Software, "Industrial Internet," keynote presentation at the INFORMS Conference on Analytics & Operations Research, April 12-14, 2015, Huntington Beach, CA.
27. Davenport (2009), op. cit.
28. David Kiron, Renee Boucher Ferguson, and Pamela Kirk Prentice, "From Value to Vision: Reimagining the Possible with Data Analytics," *MIT Sloan Management Review Research Report*, March 5, 2013.
29. Davenport (2009), op. cit.
30. Davenport and Harris (2007), op. cit.
31. Victor Mayer-Schönberger and Kenneth Cukier, *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Boston, MA: Houghton Mifflin Harcourt, 2013).
32. Mary Siegried, "Find the Big Picture in Big Data," *Inside Supply Management*, (January/February 2014), pp. 19-23. Also available at <https://www.instituteforsupplymanagement.org/pubs/ISMMag/ismarticle.cfm?ItemNumber=24235 >.
33. Mayer-Schönberger and Cukier, op. cit.
34. Davenport and Harris (2007), op. cit.; Cindy Etsell, "Analyze This: Enhancing Operational Excellence through Customer Data," *Digital Manufacturing*, February 15, 2012.

35. M.A. Huselid and B.E. Becker, "Bridging Micro and Macro Domains: Workforce Differentiation and Strategic Human Resource Management," *Journal of Management*, 37/2 (March 2011): 421-428.
36. M.R. Leenders, P.F. Johnson, A.E. Flynn, and H.E. Fearon, *Purchasing and Supply Management* (New York, NY: McGraw-Hill, Irwin, 2010), p. 6.
37. Brad Stone, "The Secrets of Bezos: How Amazon Became the Everything Store," *Bloomberg Businessweek*, October 10, 2013, <www.businessweek.com/articles/2013-10-10-/jeff-bezos-and-the-age-amazon-excerpts-from-the-everything-store-by-brad-stone>.
38. Shel Israel, "How Walmart and Heineken Will Use Shopperception to Put Your In-Store Experience in Context," <www.forbes.com>, January 27, 2013.
39. Nigel Hollis, "Starbucks' New Logo: A Risky Move," HBR Blog Network, January 7, 2011, available at <www.blogs.hbr.org/2011/01/starbucs-new-logo-apple-or-le/>.
40. "Data, Data Everywhere," *The Economist*, February 25, 2010.
41. A great deal has been written about Walmart's unifying platform Retail Link. Some good sources are: Mayer-Schönberger and Cukier, op. cit.; "A Different Game," *The Economist*, February 25, 2010, available at <http://www.economist.com/node/15557465>; Sam Hornblower, "Always Low Prices," <www.pbs.org/wgbh/pages/frontline/shows/walmart/secrets/pricing.html>.
42. Marshall L. Fisher and Ananth Raman, *The New Science of Retailing: How Analytics are Transforming Supply Chains and Improving Performance* (Boston, MA: Harvard Business Press, 2010); Marshall L. Fisher, Ananth Raman, and Anna McClelland, "Rocket Science Retailing Is Almost Here: Are You Ready?" *Harvard Business Review*, 78/4 (July/August 2000): 115-124; F. Caro and V. Martínez-de-Albéniz, "How Fast Fashion Works: Can It Work for You, Too?" *IESE Insight*, 21 (Second Quarter 2014): 8-65.
43. Christopher Bjork, "Zara Builds its Business around RFID," *Wall Street Journal*, September 16, 2014, pp. B1-B2.
44. Caro and Martínez-de-Albéniz, op. cit.; Sunil Chopra "Seven-Eleven Co., Japan," Kellogg School of Management, February 2005.
45. Caro and Martínez-de-Albéniz, op. cit.; Sunil Chopra, op. cit.
46. Barton and Court, op. cit.
47. Mayer-Schönberger and Cukier, op. cit.
48. J. Maniyaka et al., "Big Data: The Next Frontier for Innovation, Competition, and Productivity," McKinsey Global Institute, May 2011.
49. "Coke Has a Secret Formula for Orange Juice, Too," *Bloomberg Businessweek*, February 4, 2013, pp. 19-21.
50. Marshall Fisher, "What is the Right Supply Chain for Your Product?" *Harvard Business Review*, 75/2 (March/April 1997): 105-116.
51. M.E. Porter, "From Competitive Advantage to Corporate Strategy," *Harvard Business Review*, 65/3 (May/June 1987): 43-59; M.E. Porter, "What Is Strategy?" *Harvard Business Review*, 74/6 (November/December 1996): 61-78; M.E. Porter, *On Competition* (Boston, MA: Harvard Business School Publishing, 1998); R.H. Hayes and S.C. Wheelwright, "Link Manufacturing Process and Product Life Cycles," *Harvard Business Review*, 57/1 (January/February 1979): 133-140.
52. Davenport (2009), op. cit.
53. <https://www.adobe.com/content/dam/Adobe/en/customer-success/pdfs/americaneagle-case-study.pdf>.
54. "FordDirect Debuts DealerConnection Elite Service for Dealers at the National Automobile Dealers Association (NADA) Convention," *PR Newswire*, February 4, 2012.
55. Masaaki Imai, *Gemba Kaizen* (New York, NY: McGraw-Hill, 2007).
56. Travis Hessman, "Putting Big Data To Work," *Industry Week*, 262/4 (April 2013): 14-18.
57. This is a number with 10^{24}. Essentially it is a huge amount of data.
58. Manyika et al., op. cit.; Basel Kayyali, David Knott, and Steve Van Kuiken, "The Big-Data Revolution in US Health Care: Accelerating Value and Innovation," *McKinsey & Company*, April 2013.
59. Oliver Bossert, Wolf Richter, and Allen Weinberg, "Protecting the Enterprise with Cybersecure IT Architecture," *McKinsey & Company*, March 2015.
60. Manyika et al., op. cit.; Kayyali, Knott, and Van Kuiken, op. cit.
61. N.R. Sanders and A. Locke, "Making Sense of Outsourcing," *Supply Chain Management Review*, 9/2 (2005): 38-45.
62. Robert McMillan, "Offshore Outsourcing Cited in Florida Data Leak," *Computerworld*, March 26, 2006; Saritha Rai, "Security Breaches Worry Outsourcing Industry," *The New York Times*, October 5, 2006; "The Leaky Corporation," *The Economist*, February 24, 2011.

63. Paula Rosenblum, "Target Hit by One of Most Sophisticated Data Thefts Ever, But It Won't Hurt the Retailer," *Forbes*, December 19, 2013; N. Eric Weiss and Rena S. Miller, "The Target and Other Financial Data Breaches: Frequently Asked Questions," Congressional Research Service, February 4, 2015, <www.crs.gov>.
64. Stephanie Overby, "IT Service Providers and Customers Battle Over Data Breaches," *CIO Magazi*ne, March 9, 2012; "Outsourcing Risk: Who Pays Most When Customer Data is Breached?" *W.P. Carey Magazine*, Spring 2015.
65. Thor Olavsrud, "IBM Unveils Industry-Specific Predictive Analytics Services," *CIO Magazine*, May 28, 2015.

California Management Review, Vol. 58, No. 3, pp. 26–48. ISSN 0008-1256, eISSN 2162-8564. DOI: 10.1525/cmr.2016.58.3.26.