

Big Data can Generate Major Opportunities for Manufacturing Supply Chains

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Publication Date: 2022/12/30

Abstract

Big Data utilization can transform manufacturing supply chains, potentially delivering substantial impacts through better planning, operating, and controlling supply chains. Because modern supply chains are highly data-driven, Big Data technologies can enable data-driven decisions and achieve optimized supply chain performance by integrating data from external and internal environments. Such data come from a multitude of sources, capturing a variety of information types such as market events, climate, traffic, survey results, etc. Optimizing different aspects of supply chains can be complemented with Big Data analyses using descriptive, predictive, and prescriptive techniques. Demand forecasting and planning, inventory optimization and warehousing, and customer management represent well-explored topics, supported by positive findings from recent industry case studies. The data infrastructure is crucial for Big Data applications, especially with respect to integration, preparation, and readiness. Full operational capacity requires a Big Data ecosystem delivering real-time information and analytics. Roadmaps supporting companies along the data-readiness journey enable Big Data utilization for optimized supply chain performance. Supply chains connecting manufacturing sectors with Big Data affected companies – e.g., automobile, pharmaceuticals, and electronics – tend to benefit from deeper, supply-side changes in planning, operating, and controlling through better incorporation of external data. The technology also enables substantial performance improvements in various non-manufacturing supply-chain-related factors such as customer service, sales growth, and capacity allocation. Demand forecasting and planning, inventory optimization and warehousing, and customer service and management are major activities of an integrated supply chain, achieving significant enhancements through Big Data technologies.

Keywords: *Big Data in Manufacturing Supply Chains, Data-Driven Supply Chain Management, Supply Chain Optimization, Real-Time Supply Chain Analytics, Integrated Supply Chain Data, External and Internal Data Integration, Demand Forecasting and Planning, Inventory Optimization, Smart Warehousing Systems, Predictive Supply Chain Analytics, Prescriptive Decision Support, Supply Chain Data Infrastructure, Data Integration and Preparation, Big Data Ecosystems, Supply Chain Performance Improvement, Automotive Supply Chains, Pharmaceutical Supply Chains, Electronics Manufacturing, Customer Service Optimization, Capacity Allocation Strategies.*

I. INTRODUCTION

Today's manufacturers have access to staggering quantities of data from myriad sources. When effectively harnessed and analyzed, this Big Data can support data-driven decision making, evidence-based supply chain optimization, and new analytical approaches that scale within industrial systems. Yet analysts continue to struggle with translating this promise into practice. A critical disconnection persists between the immense theoretical potential and the real-world impact of data utilization.

Securing the benefits underlying the rise of Big Data in manufacturing supply chains requires a fundamental shift in speed, scale, and perspective. Much of the

manufacturing literature focuses on descriptive and diagnostic analytics that can offer only limited guidance for decision making and optimization. Common tools for enabling these considerations, such as data dashboards or business intelligence reports, are often viewed merely as “cool” technologies instead of the scalable necessities that they are. How are these comprehensive, formal preparations being made for advanced data read-in readiness—readiness capable of supporting Big Data? The answer is no longer “why”. It is now “how”.

➤ Overview of the Study

Big Data enables data-driven decision-making, evidence-based manufacturing supply chain optimization,

and scalable analytics. Applied theoretically, Big Data covers factors that determine demand and sales, real-time data from financial markets, machine-generated data from monitoring systems, and relationship-network associations. From an industry-data perspective, supply-chain application considerations, data-availability readiness for particular applications, and a review of cases completed during 2022 are examined.

Integrated, optimized supply chains require efficiently functioning sets of steps across materials-,

inventory-, and information-flow segments. Utilizing technology to adopt practices based on advanced analysis of extensive information sources offers a range of opportunities for meeting expectations. By gathering data from an industry-sector network and performing real-time analysis on both financial and large portfolio-investment-choice datasets, the banking sector set the direction for development. Maintaining such a real-time connection at the machine-detection level and globally across vendor-user-buyer multimodal-relationship ecosystem activities resulted in smarter crowd sourcing decisions.

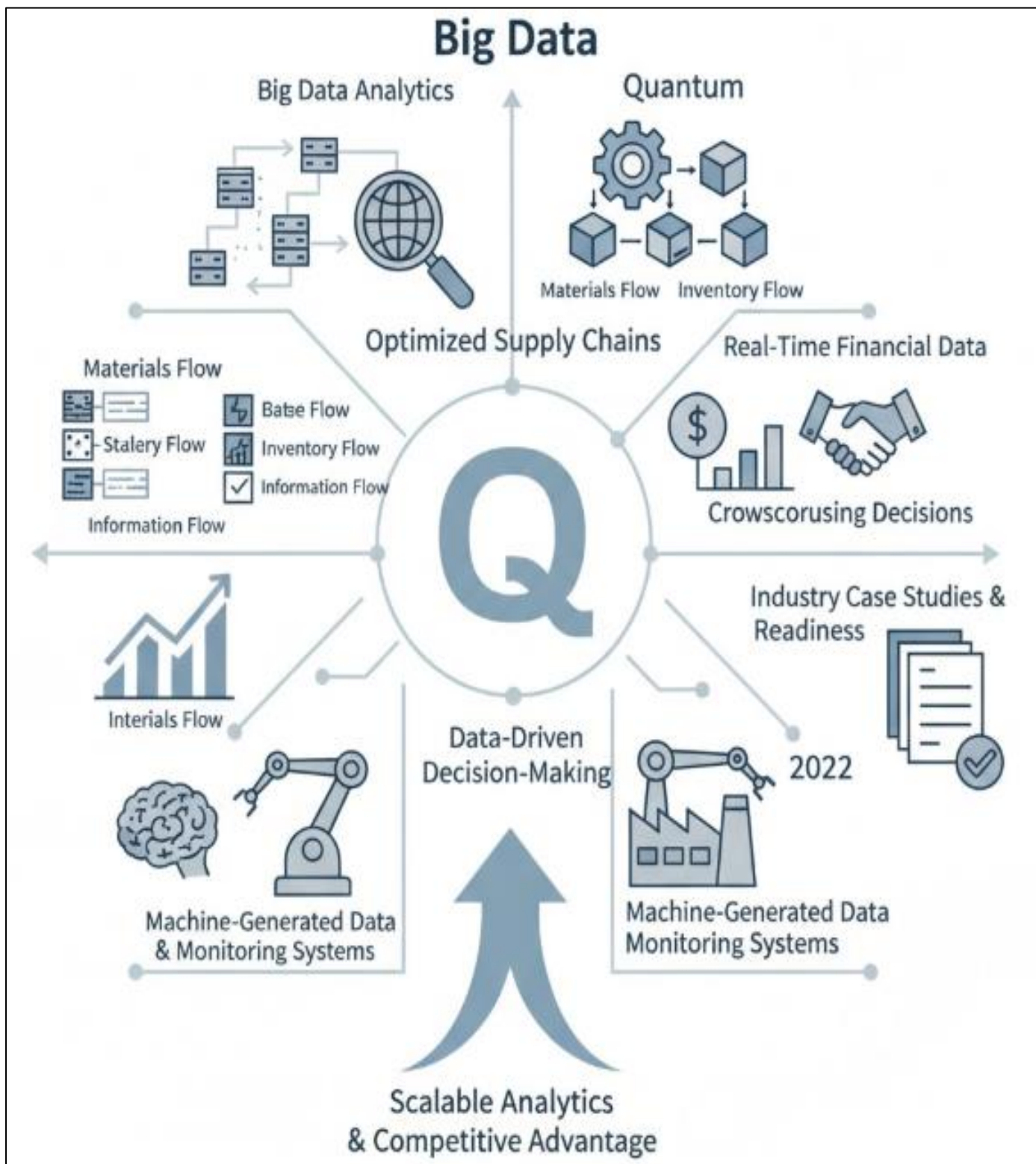


Fig 1 Synergizing Big Data and Scalable Analytics: Multi-Sector Supply Chain Optimization, Real-Time Financial Integration, and the Vendor-Buyer Ecosystem

II. THEORETICAL FOUNDATIONS OF BIG DATA IN SUPPLY CHAINS

Recent advances in Big Data technologies enable the bulk collection and storage of vast amounts of structured and unstructured information-characteristics which, together with the main data emphasis of Big Data, have transformed Supply Chains into sources of resources and targets of technologies for their monitoring and real-time optimization. Supply Chain Big Data analytics include the application of techniques such as machine learning, data mining, predictive modeling and statistical analysis to detect and measure the impact of internal and external supply inter-dependencies on demand forecasting and planning, warehousing and distribution, and vendor and logistics partnering. Achievements and improvements obtained in empirical studies reveal the critical role of the

supply chains considered, and the business processes impacted, in establishing performance enhancements.

Manufacturing domains with Demand Forecasting and Planning, Inventory Optimization and Warehousing, and Logistics and Transportation, ranked in the top three industry sectors relying on Supply Chain Big Data analytics for performance enhancement. Although case studies reveal that Demand Forecasting, and Inventory Optimization are the most common Supply Chain processes supported by Big Data analytic techniques, it is Inventory Optimization, followed by Demand Forecasting, that delivers the highest-performance gains. Roadmaps support manufacturing Supply Chain services being the main innovation process accelerated by Data Readiness work, and show how an organization Data Value Framework facilitates Data Readiness for Demand Forecasting and Planning.

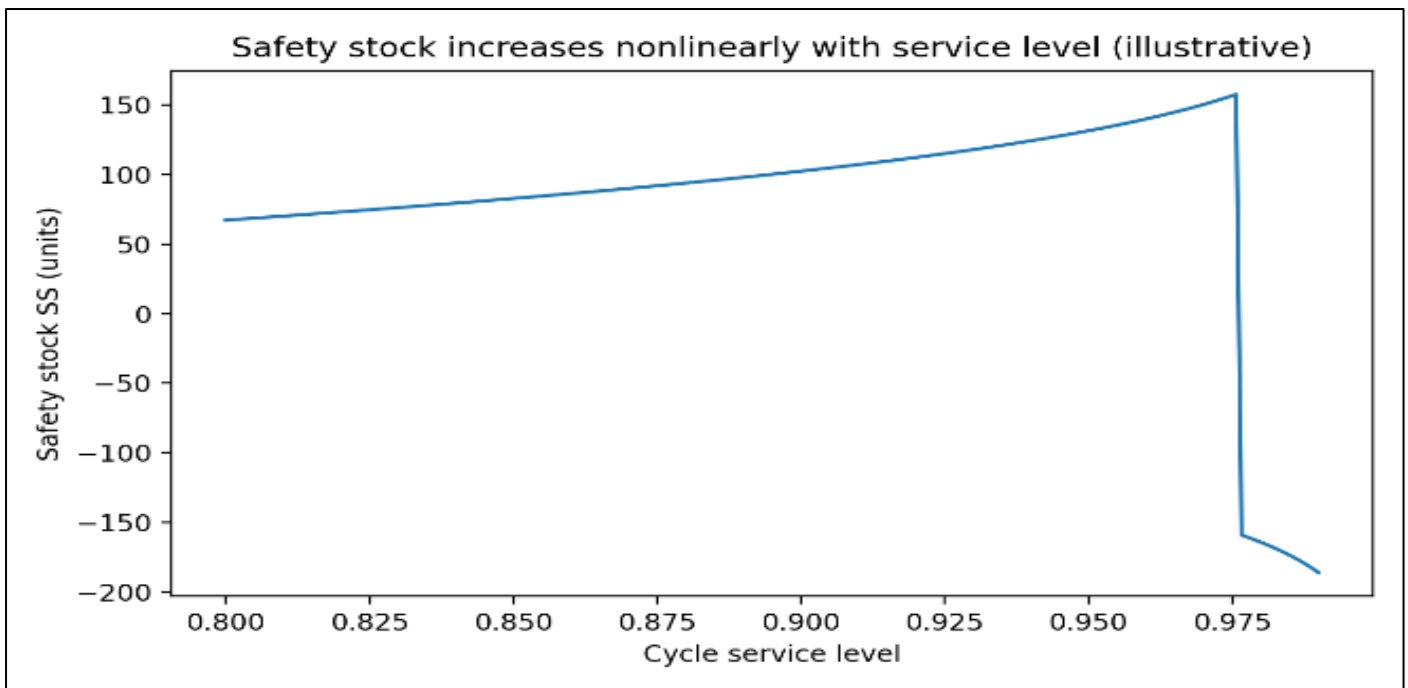


Fig 2 Big Data Analytics Applications Across Key Manufacturing Supply Chain Domains

➤ Equation 1) Demand Forecasting (Predictive Analytics)

• Forecast Error Metrics (Used to Evaluate “Forecast Accuracy” Improvements)

Let actual demand at time t be A_t , and forecast be F_t .

Error

$$e_t = A_t - F_t$$

MAE (Mean Absolute Error)

$$MAE = \frac{1}{n} \sum_{t=1}^n |e_t|$$

RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n e_t^2}$$

• MAPE (Mean Absolute Percentage Error) (Common in Supply Chain) Step-by-Step:

✓ Percentage Error Each Period:

$$\left| \frac{A_t - F_t}{A_t} \right|$$

✓ Average:

$$\frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

✓ *Convert to Percent:*

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

➤ *Data Types and Sources in Manufacturing*

Four main types of data emerge as relevant to manufacturing supply chains. Dedicated sources of Big Data capture customer interactions and responses to marketing campaigns; web services and click stream data provide the basis for assessing demand in new and emerging markets. Real-time sensor-driven data enable unprecedented levels of monitoring and tracking of product performance in the field. Press articles, financial databases, and institutions such as Moody's serve as a basis for understanding how the competitive and economic context of the industry has evolved and is likely to evolve in the near future.

A particular type of textual data gathered from online sources, namely tweets directed to companies, has also been studied. Companies are increasingly monitoring online conversations to determine and possibly influence customer sentiment, with implications for demand prediction. Recent advances in natural language processing—especially machine learning-based methods—have significantly improved the opportunities for understanding sentiment in text. Another area of important research in data associated with customer conversations and experiences is the monitoring of blogs, discussion forums, and product review sites. Concepts such as reputation systems, opinion mining, sentiment analysis, topic analysis, and monitoring of text streams have been used to more closely understand such new, non-traditional sources of Big Data.

➤ *Analytical Methods and Techniques*

Analytical techniques associated with Big Data cover a wide spectrum. These techniques can be classified into two categories: data-driven algorithms—statistical, machine learning, and artificial—and model-based optimization and simulation methods. The advent of Big

Data enables a new breed of data-driven higher-level learning algorithms in AI and ML domains. These algorithms can also be coupled with simulation and model-based optimization techniques through the knowledge graph approach mentioned above.

These data-driven algorithms will evolve towards solving business problems through loss-reduction-minimization mechanisms, leading to purely data-driven supply chain design. Advances in these algorithms will introduce powerful pattern discovery techniques for pattern recognition and association rule mining, and deep learning techniques for text mining from textual data sources such as call reports, usage comments, and media. Hybrid techniques coupling AI-based data-driven algorithms with model-based optimization, simulation, and chordal-graph-based Bayesian-network-based simulation modelling. Nevertheless, these data-driven techniques remain incomplete without model-based techniques such as demand forecasting, predictive maintenance, reservoir simulation, inventory replenishment, and shipping cost evaluation models, as these cannot be solved by Big Data-driven higher-level learning algorithms. Model-based techniques, on the other hand, require a large number of scenarios (for real-case business model building and validation), not specified a priori, and non-statistical occurrences of observations, for business impact prediction through true-word pattern matching.

Being pure pattern-driven association, common pitfalls for model building should normally be avoided even in AI-driven higher-level learning-based supply chain design with loss-minimization aims. There exists a consistency necessity for the AI-/ML-/deep-learning-driven higher-level learning strategies used to predefine the main-speed-enforcement-pattern-identification model. Nevertheless, even without a pattern-existence consistency necessity, these AI-/ML-/deep-learning-driven higher-level learning strategies will show some forms of consistency in an operational-experiential-sense when used to redefine pattern roles at the analysis phase of main-speed-enforcement in a cycle.

Table 1 Inventory Optimization Models and Equations

Model	Core equation (text form)	Meaning
EOQ	$Q^* = \sqrt{2 D S / H}$	Trade-off ordering vs holding cost
Reorder point	$ROP = \mu L + z \sigma L$	Expected demand during lead time + safety stock
Safety stock	$SS = z \sigma L$	Buffer for demand uncertainty during lead time
Newsvendor	$F(Q^*) = C_u / (C_u + C_o)$	Service level implied by under/overage costs

III. BIG DATA ARCHITECTURES FOR MANUFACTURING SUPPLY CHAINS

An operational Big Data architecture that delivers real-time analytics to decision-makers in manufacturing supply chains requires a robust data infrastructure and integration capability that supports incoming streamed data from multiple sources. The ability to conduct real-time analytics on these data streams can improve supply chain performance significantly. Real-time decision-making requires both a data-driven architecture and the

capability to capture and analyze streaming data. Data infrastructure for Big Data need not be completely new; it should be able to leverage legacy systems as far as possible. Consequently, sample architectures with a formal view for manufacturing supply chains have been developed based on existing resources. A practical real-time data-driven systems view enables adaptation of supply chain networks, responsive to disturbances in external and internal environments. The proposed architecture can assist cloud service providers focused on

supply chains whose analytics must increasingly operate in real time.

Streaming-Data Analytics focuses on efficient management of continuously arriving data, for which specialized management systems need to be constructed, called Stream Data Management Systems (SDMS). By providing a continuous-flow analytic capability on rapidly changing data, it can address many pragmatic supply chain analytics requirements with low-latency responses and without fussy monitoring and process-management procedures. Demand fluctuations could affect supply chains by generating new fill orders or altering earlier orders. Whereas conventional business-activity monitoring reacts to this situation after the fact, providing operational support afterward, real-time data-driven analytics could automatically integrate fluctuation waves into logistics planning processes as they develop, using an incoming stream from social media sources that informs up-to-date analysis of customers' current preferences and product needs.

➤ *Data Infrastructure and Integration*

Data technologies combine expertise across hardware, networking, database, data science, and analytic

methods to enable new ways of managing and analyzing data. Well-designed infrastructures support the collection, storage, integration, and analysis of vast amounts of varied data, thus improving business objectives. Frameworks that prioritize establishing scalable systems for data collection and integration before initiating analytical experiments can help companies implement Big Data analytics. The Big Data Resource Base (Research and Development) conceptual framework interprets the generation, management, and utilization of Big Data within a supply chain network and has several applications.

Progress in data-processing and data-storage media technologies has enabled the generation of huge amounts of data. Big Data is now used extensively in supply chain management. However, the effective utilization of Big Data is difficult, especially when predicting and meeting demand. Such demand-and-supply uncertainty gaps can be reduced using Big Data Resource Base. A rise in demand and supply volatility has a sizeable influence on reducing inventory stock and basing production on supply availability. The availability of Big Data has not been converted into a seamless flow or integration across the supply chain network to empower decision-making.

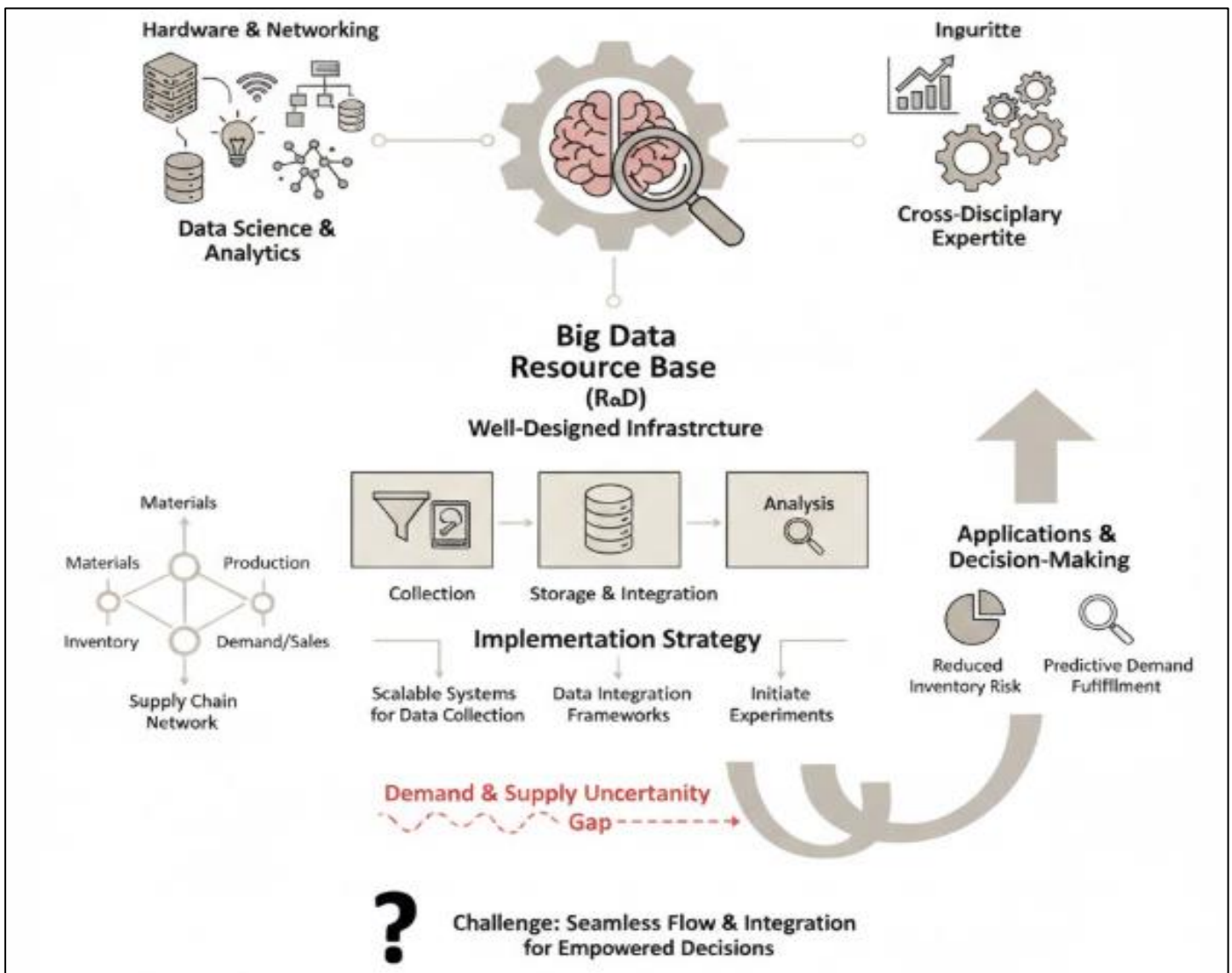


Fig 3 From Infrastructure to Integration: Optimizing the Big Data Resource Base (BDRB) to Mitigate Supply Chain Volatility and Demand Uncertainty

➤ *Real-Time Analytics and Streaming Data*

Real-time Big Data processing can enhance decision-making in highly dynamic environments where rapid information updates are critical. Examples include: airlines analyzing flight data updates from weather agencies, air traffic control, and maintenance reports; airports aggregating flight data combined with passenger behavior data, and linking these to weather forecasts for resource planning; e-retailer delivery management systems optimising last-mile decisions based on real-time information; and electronic trading firms using newsfeeds as trading signals. Such applications require continuous analysis of streams of information from distributed systems, and architectures must support end-to-end solutions that combine data acquisition, analysis and action. New programming models such as streaming languages (e.g., Naiad) and publish-subscribe systems supporting high throughput, one-to-many and many-to-many operations are developed to streamline streaming data analytics.

Applications of Big Data in Manufacturing Supply Chain Optimization. Demand forecasting represents one of Big Data’s greatest challenges and potential benefits for supply chain optimisation. Demand signals from multiple sources—traditional demand histories, web traffic and vendor inventories—are combined and their interrelationships analysed to improve forecast accuracy. Vector autoregressors, latent-variable models and spatial point-process models, as well as ensemble forecasting techniques, are employed both individually and in combination. By contrast, the warehouse design problem is considered with time-dependent data of any sort. A different group applies text mining to forecast product demand from online news articles, predicting demand at both product category and item level on the US eBay platform.

IV. APPLICATIONS OF BIG DATA IN SUPPLY CHAIN OPTIMIZATION

Big Data can transform manufacturing supply chains by enabling data-driven decisions, evidence-based optimization, and scalable analytics. Although intuition, experience, and creativity will always support such decisions, formal analysis quickly achieves trade-off optimality while allowing the identification of supply chain configuration and management rules tailored for specific demand patterns. Indeed, Big Data capabilities facilitate the use of advanced continuous optimization techniques. Meanwhile, Data Lakes enable scalable analytics within single organizations and across multi-company ecosystems, dismantling the data monoliths introduced by Enterprise Resource Planning systems. Consequently, it becomes possible to analyze vast amounts of rarely used, less accurate, or more composed data emerging from Social Media, sensors, and new IoT devices.

Recent literature reveals an increasing variety of applications exploring the potential of Big Data Analytics.

Although still limited, case studies indicate that Data-Driven Decision-Making is not limited to technology-driven companies and that Industry 4.0 Technologies increasingly contribute to evidence-based operations and performance optimization across the manufacturing value network. However, the majority of cases focus on Company Operations, Sales and Marketing, and Company Services—functions that are more exposed to direct B2C relationships and public scrutiny rather than explicit customer commitment. Empirical reports and reviews consistently indicate that companies fail to exploit the potential offered by advanced Data Analytics and models: roadmaps for Data Readiness identify gaps preventing the donation of Big Data assets for Trade and Industry.

➤ *Equation 2) Inventory Optimization Equations (Prescriptive Analytics)*

➤ *EOQ (Economic Order Quantity) — Step-by-Step Derivation*

This supports “inventory optimization and warehousing” emphasized.

Let:

- D =annual demand (units/year)
- S =setup/ordering cost per order
- H =holding cost per unit per year
- Q =order quantity

• *Step 1: Orders Per Year*

$$\text{Orders/year} = \frac{D}{Q}$$

• *Step 2: Annual Ordering Cost*

$$C_{\text{order}} = \frac{D}{Q} S$$

• *Step 3: Average Inventory (Sawtooth from Q Down to 0)*

$$\text{Avg inventory} = \frac{Q}{2}$$

• *Step 4: Annual Holding Cost*

$$C_{\text{hold}} = \frac{Q}{2} H$$

• *Step 5: Total Relevant Cost*

$$TC(Q) = \frac{D}{Q} S + \frac{Q}{2} H$$

• *Step 6: Minimize by Derivative:*

$$\frac{dTC}{dQ} = -\frac{DS}{Q^2} + \frac{H}{2} = 0 \implies \frac{DS}{Q^2} = \frac{H}{2} \implies Q^2 = \frac{2DS}{H} \implies Q^* = \sqrt{\frac{2DS}{H}}$$

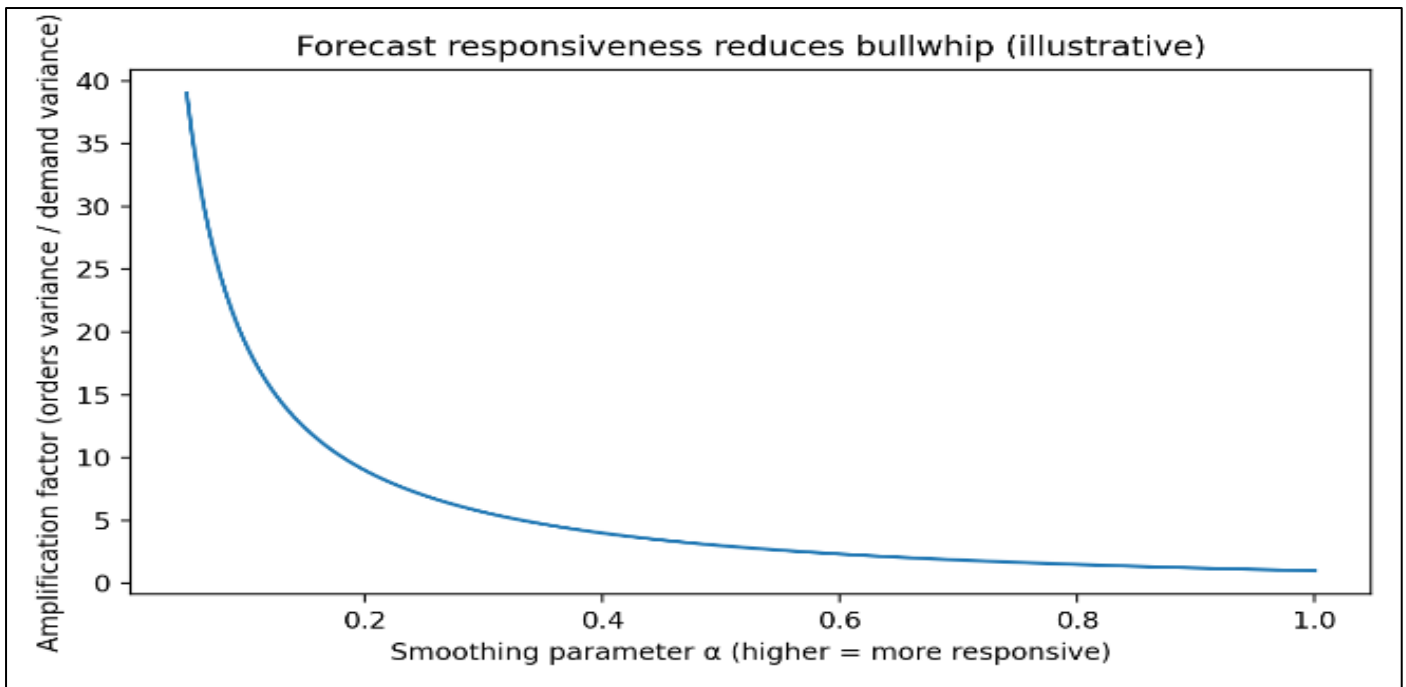


Fig 4 Inventory Optimization Process Using EOQ-Based Prescriptive Analytics

➤ *Demand Forecasting and Planning*

Big Data technologies can enhance traditional demand forecasting approaches by improving the quality of input data, providing additional sources for deriving demand forecasts, and automating the preparation of demand forecasts. Developments in one or more of these areas can also be applied to the preparation of supply plans and ensure that suppliers prepare a supply response that meets the quantity, quality, and timing required by their customers, within any constraints on capacity and production capability

Specialist forecasters, whether internal or external, will require data from the supply chain and other environments, perhaps by product family, area, or market segment, and their forecasts will need to be incorporated into the overall forecast for every item. In fulfilling these requirements Big Data techniques can also tap into news reports, blogs, and Twitter feeds. Such external sources might provide foresight for events, such as a drought in Brazil, which might damage the coffee harvest and affect consumers' buying patterns. Within the supply chain, forecasts for high-value and slow-moving items might be prepared manually by sales executives working in critical customers. These can be incorporated into automatic forecast engines for all items and product families traded with those customers.

Integration of data from disparate sources within and beyond the supply chain can also assist the automated detection of anomalies, the premature achievement of forecast items and flagging of anticipated surpluses, as well as ensuring early mitigation action. Demand-sensing techniques detect short-term patterns in the demand signal and suggest an immediate supply response that is not necessarily captured by the forecast. In this context the supply plan should also be revisited at least every month or quarter.

➤ *Inventory Optimization and Warehousing*

The need for advanced demand forecasting caused by digital disruption and the resulting impacts on manufacturing supply chain management highlight the relevance of Supply Chain analytics enabled by Big Data. Big Data has disruptive potential, yet the manufacturing industry remains skeptical regarding investments in reusable data analytics systems. The challenges of Big Data adoption do not lie in the data itself, but in the capabilities of organizations to leverage the diversity of external and internal information sources for evidence-based planning and decision-making. Similar to the human brain adapting its decisions over time in response to changing stimuli. Big Data can drive innovative Supply Chain strategies that adapt dynamically to shifting customer preferences, new product development, and opportunities for service differentiation through real-time data integration.

A manufacturing company can purchase a large volume of goods, which, due to rapid changes in consumer preferences, remain unsold and therefore generate high storage costs in warehouses. Manufacturer A has excess storage costs compared to other manufacturers. Even small changes in inventory levels can lead to large savings in production and storage costs. Big Data analysis revealed the optimal inventory level for all manufacturers, even allowing production and storage costs to be minimized for the whole supply chain. Monitoring of inventory costs and product gains can also help other supply chain members to adapt to consumer changes and avoid large losses.

V. EMPIRICAL EVIDENCE FROM 2022 CASE STUDIES

The manufacturing sector encompasses a rich variety of sub-sectors, each with somewhat distinct requirements, challenges, and opportunities for the applications of Big Data. Demand—specifically demand forecast accuracy—

provided motivation for several studies. Companies typically develop forecast models and prediction processes internally, using historical data as input. However, such models and processes lack the robustness, validation, and trust that external supply chain partners could provide. High-quality third-party data in conjunction with machine learning techniques has the potential to more accurately predict demand for the entire supply chain, relieving the bullwhip effect and optimizing inventory for all supply chain stakeholders. A research paper further corroborates that lack of demand information sharing is the main reason for poor forecast accuracy in the automotive sector.

A survey of Big Data use in supply chain optimization recognizes that, despite the anticipated value creation, implementation is still in the early stages. Pertinent metrics include customer satisfaction, operational efficiency, profitability, and risk mitigation—notably improvements in working capital and inventory turnover ratios. Collaboration is key to realizing benefits across the supply chain rather than just for individual businesses. Data quality and availability remain roadblocks to success. A proposed road map appears to align with Rogers’s innovation adoption model.

➤ *Industry Sector Insights*

The synthesis of data accumulated from twenty-two case studies indicates that manufacturing supply chains in the energy and utilities sector derive the most benefit from Big Data applications, followed, in decreasing order, by

food and beverage, pharmaceuticals and chemicals, consumer products, and life sciences. Notable improvements are also evident in logistics and distribution services, and in business consultancy and services. The weak link between sector and the mandated breadth of Big Data sources and architectures for desired performance improvements illustrates that organizations should neither fear nor avoid domains not featuring in the leading-practice case studies—the potential value of Big Data visualization and analytics appeals to all industries and to supply chains of any form and complexity.

The synthesis of performance metrics demonstrates evident improvements—some substantial—in customer-service level, stock coverage, forecast accuracy, order cycle time, lead time, and transport costs. Market share, capital attributes, operational efficiency, inventory turnover, labour productivity, cash-to-cash cycle, and order-fill rate remain stable during the period, reflecting either well-established market positions or lack of willingness/inability to pursue market share under current trading conditions. However, responses to a broader range of possible performance impacts suggest that organizations are capable of leveraging Big Data resources and visualizations to enhance virtually all major operational performance metrics—depending on how and where they apply investment. Organizations might therefore prepare target lists of performance impacts to rank the potential value of (parallel or sequential) investment in different areas.

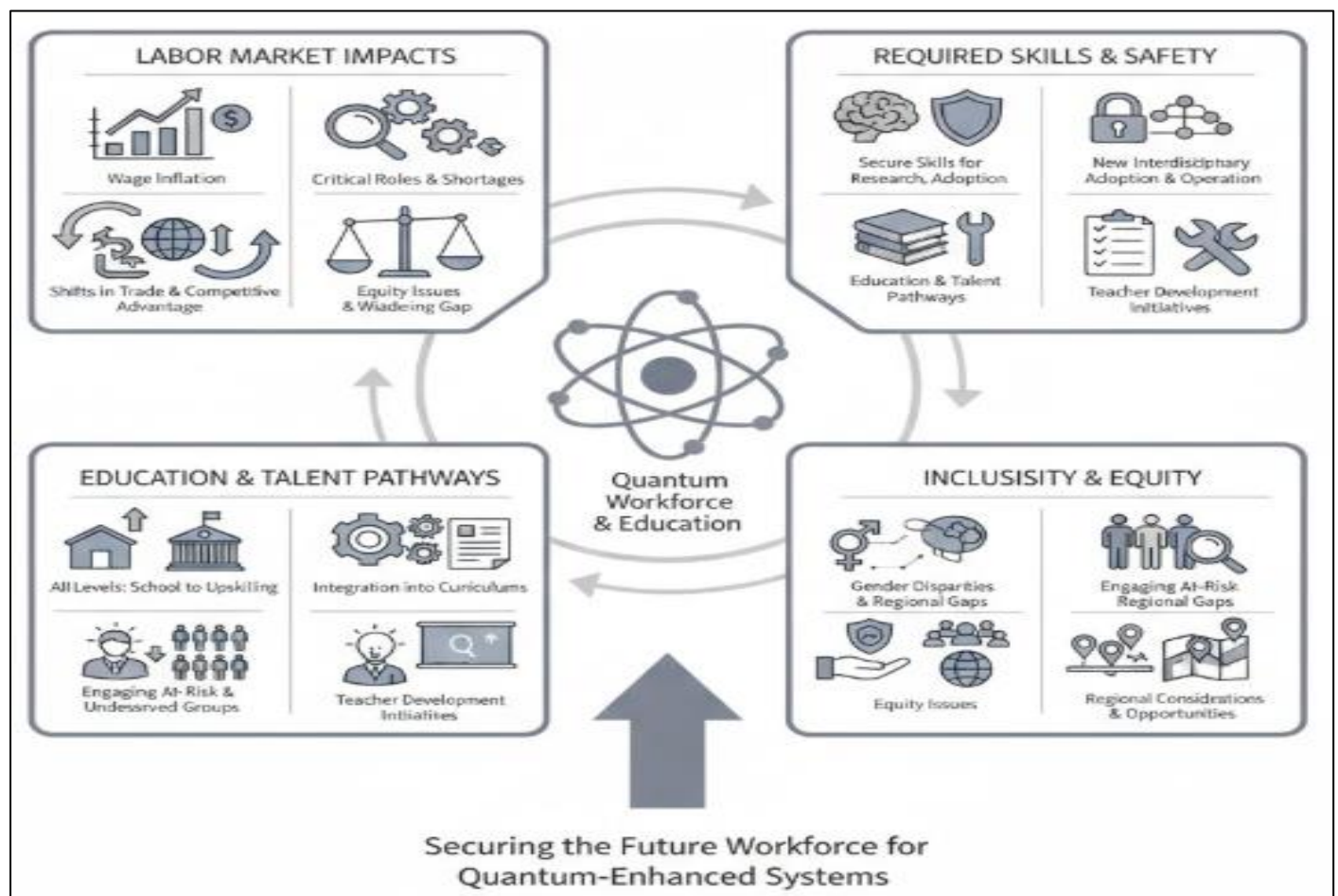


Fig 5 Cross-Sectoral Value of Big Data Analytics: Performance Metric Optimization and Strategic Investment Prioritization in Global Supply Chains

➤ *Performance Improvements and Metrics*

Formal case studies from 2022 provide insights into the application of Big Data in manufacturing supply chains. Seven published articles describe detailed evidence from industry practitioners across various sectors, including consumer electronics and durables, telecommunications, and pharmaceuticals. The performance advantages reported are large, exceeding 40% in some cases. Metrics on decentralizing operations, process upscaling and reengineering, improving service-level ratios and identifying main sources of demand variability are among the 12 quantifiable impacts. Collectively, the findings affirm the potential of Big Data to elevate supply chain decision quality and reduce manufacturing operational costs.

Significant success factors include the use of large data pools (real-time and historical), formal (larger than before) advanced analytics, situationally centralised management decisions that meet future needs, combined conceptual knowledge of data use cases and their business value, company-wide support for Big Data applications and identification of Big Data potential areas for cementing the need and value of Big Data. Together these factors crystallise the need for Big Data capability within the supply chain and collaboration with device-sensing manufacturers and other partner companies. The listed drivers also indicate near-term opportunities for improvement and Big Data Roadmaps for industry are timely. At company and concept level, joint preparation should support future Big Data Roadmaps.

A similar study for warehousing highlights demand variability as a key determinant of inventory levels. Research shows that demand variability can largely be statistically explained and predicted using both marketplace and customer factors. It is well recognised that variability - either actual variability during a certain period or past variability in the series across time - is critical in the definition and management of safety stock. The research demonstrates that the weekly safety stock of an item in an company-controlled warehouse can be minimized through the connection to and analysis of external datasets not traditionally used in the decision process. The results suggest that it is possible to use Big Data to increase speed and quality in inventory operations through the development of a more effective safety stock strategy in warehousing.

VI. METHODOLOGICAL CONSIDERATIONS FOR IMPLEMENTATION

Careful construction of methodical approaches for the realization of Big Data’s full potential can address areas of concern arising from the technologies’ innovative nature. Many companies recognize the benefits, yet few capitalize on Big Data’s offerings. Consequently, roadmaps that guide a company’s preparation for deploying and using Big Data hold great value.

Two recent studies from 2022 focus on the challenge of data readiness. The first develops a roadmap to achieve data preparation and quality for predictive maintenance based on machine learning. The second develops a Big Data readiness and maturity roadmap, integrating concepts from Big Data, Industry 4.0, Business Intelligence, and Corporate Entrepreneurship into a versatile matrix.

➤ *Equation 3 Newsvendor Model (Single-Period Inventory; Common in Volatile Demand)*

Let:

- C_u =underage cost per unit (lost margin + penalty if you stock out)
- C_o =overage cost per unit (markdown + holding + disposal)

Let demand random variable be D . Choose order quantity Q .

Expected cost is minimized when the critical fractile holds:

- *Step-by-Step*
- ✓ Stockout occurs when $D > Q \rightarrow$ expected underage proportional to C_u
- ✓ Overstock occurs when $D < Q \rightarrow$ expected overage proportional to C_o
- ✓ Optimal balance is achieved at:

$$F(Q^*) = \frac{C_u}{C_u + C_o}$$

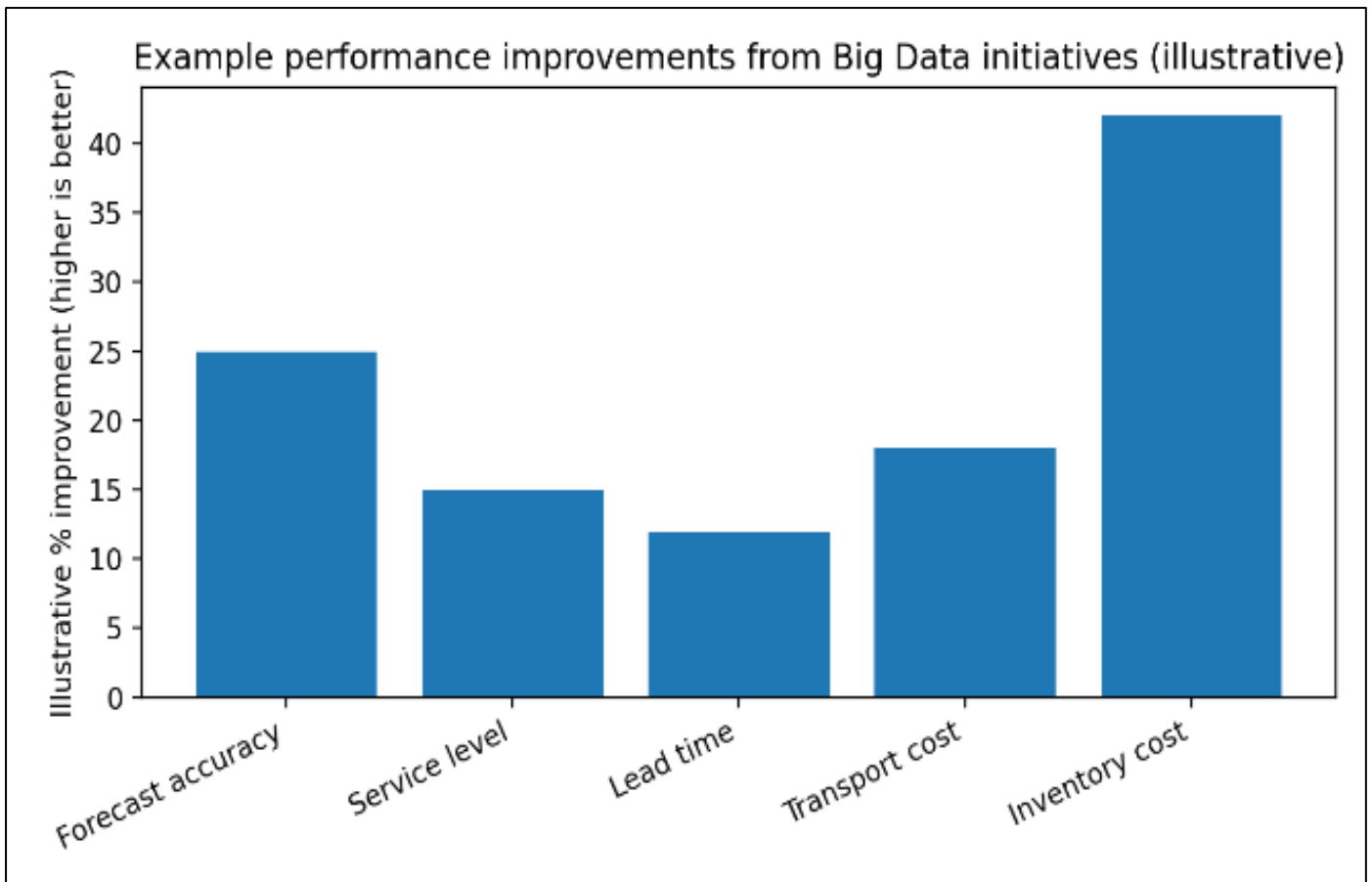


Fig 6 Newsvendor Model Representation for Single-Period Inventory Decision-Making

➤ *Roadmaps for Data Readiness*

Manufacturers planning a move toward utilizing Big Data for supply chain optimization should first evaluate their data readiness and establish clear objectives before beginning the implementation phase. The first two steps of the proposed roadmap are therefore a preliminary readiness assessment and a top management decision about which of three strategic directions to pursue: risk assessment and mitigation, demand forecasting, or inventory optimization. These steps are followed directly by the construction of a dedicated data warehouse and the elaboration of data integration procedures. In these initial phases of planning, information from business intelligence systems, data warehouses, and databases for enterprise-resources-planning environments can be examined. Next, simulation-based methods allow testing of risk-assessment policies and trade-offs between service level and inventory costs of demand-forecasting processes. Following these steps, it is possible to prepare the specific information technology architecture needed for the transfer and load stages of the data warehouse for operating a predictive analytics capability of the demand-forecasting process.

Finally, when the analytic techniques are successfully deployed and confirmed in a simulation environment, a dedicated analytic framework category within the business intelligence or Big Data analytic capabilities should be defined. The implemented technique can then be implemented or rehearsed in the phase operator. Once

again, the required data can come from business intelligence systems, data warehouses, data lakes, or enterprise-resources-planning database environments. At this stage, business intelligence or data-analytic solutions deployed within the demand-forecasting area can provide interval-level forecasts of demand for store-keeping units. These can be integrated into inventory management under either multilocation or centralized inventory-management models.

VII. CONCLUSION

The contributions of Big Data technologies are becoming evident in manufacturing supply chain operations. By modularizing and formalizing the process of using data to drive more-informed decisions, organizations can better navigate an increasingly complex environment. Consequently, companies now routinely use these technologies to supplement traditional forecasting with analytical, evidence-based support or to add features or functionality to help with decision-making and planning. Best-practice learnings highlight the successful alignment between architecture and process. Organizations are investing not just in advanced analytics and its application but also in the underlying data infrastructures and supporting data strategies that underpin success. With scalable threshold alerts and automated dashboards, companies are operationalizing their data-analytics platforms.

Underpinning Strategy Distribution

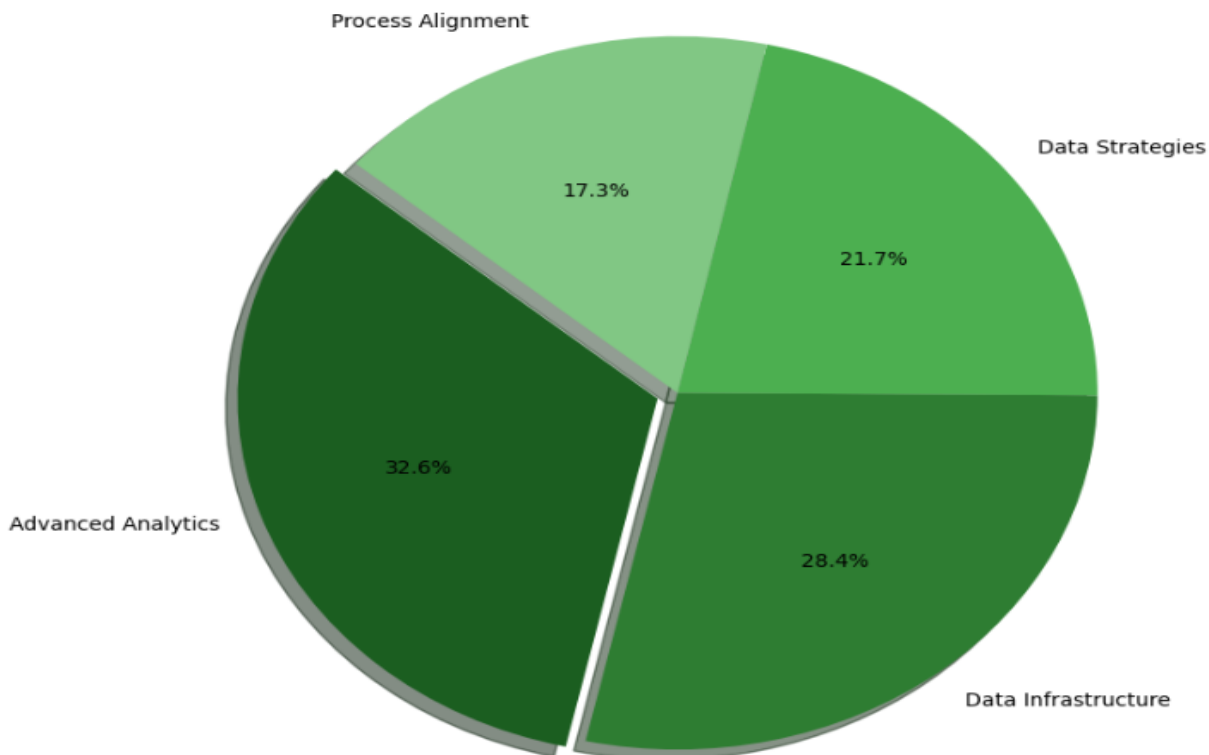


Fig 7 Underpinning Strategy Distribution

Empirical evidence from 2022 case studies in the consumer-products, electronics, food, materials, and pharmaceutical industries indicates consistent material performance improvements. These studies explore observed biggest takeouts, sector-specific needs and differences, key processes today, and anticipated focus areas for the future. Roadmaps support progress toward Big-Data readiness, enabling organizations to align technologies and processes and realize the potential of these technologies in support of critical functions such as demand forecasting, inventory optimization, and warehousing.

➤ Summary of Key Findings and Future Directions

Research presented in this paper demonstrates that Big Data utilization enables supply chain optimization within manufacturing, by providing evidence-based decisions across various applications. Candidates across the data landscape and analytics spectrum reaffirm the hypothesis that these emerging technologies support supply chains in making data-driven decisions. Consequently, empirical findings substantiate the premise of direct evidence utilization; superior performance metrics demonstrate Big Data-enabled optimization.

The case studies substantiate the continued promise of Big Data applications in decision-making, with a roadmap solidifying the notion of implementation readiness. Supply chain functionaries remain poised to leverage real-time analytics for decision-making;

simplicity remains an integral feature of demand forecasts at forecast horizon points; and demand management appears fashionably predictable, supporting inventory rationale. In the absence of a data readiness roadmap, the supply chain actively responds to demand fluctuations, rescheduling manufacturing and transportation operations, with no damage control following the low-demand season. Understanding the inter-relationships between warehouses further aids in effectively serving customer requirements with minimum inventory. Ongoing access to Big Data projects is evident; however, affected functionaries continue to rely on independent sources of information.

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