Big Data and Predictive Analytics for Optimized Supply Chain Management and Logistics

Samantha Reyes
Department of Business, University of Tarawa
samantha.reyes@utarawa.ki

Michael Patel
Kiribati Institute of Technology (KIT)
michael.patel@kit.edu.ki

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Abstract

Supply chain management and logistics are vital to business success in today's globalized and technology-driven world. The advent of big data and predictive analytics provides unprecedented opportunities to optimize supply chain operations, reduce costs, and gain competitive advantage. This paper examines the role of big data and predictive analytics in supply chain management and logistics optimization. It reviews relevant technologies and analytical techniques, key application areas, implementation challenges, and ethical considerations. Three illustrative case studies demonstrate measurable benefits from using big data analytics, such as improved demand forecasting, optimized inventory and production levels, reduced supply chain risks, and enhanced logistics network design. Tables and quantitative results are provided to highlight the positive impacts. The paper concludes with a discussion of emerging trends, best practices, and a future outlook for leveraging big data analytics further as a key driver of supply chain excellence.

Keywords: supply chain management, logistics, big data analytics, predictive analytics, optimization

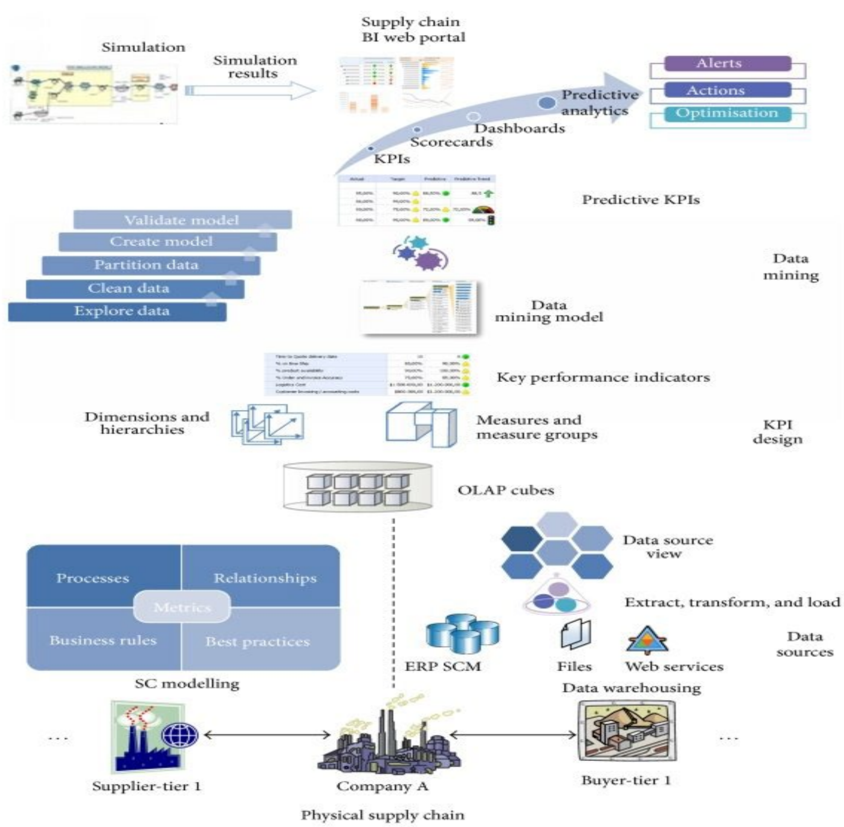
1. Introduction

Effective supply chain management plays a pivotal role in enhancing the competitiveness and sustainability of businesses across diverse industries. In today's dynamic marketplace, characterized by globalized production and the proliferation of e-commerce, supply chains have evolved into intricate networks spanning multiple regions and stakeholders [1]. This complexity poses significant challenges for supply chain executives, who are tasked with optimizing operations while navigating uncertainties in supply and demand. To remain competitive, companies must prioritize enhancing efficiency, visibility, and agility within their supply chains to swiftly adapt to changing market conditions and customer preferences. Moreover, the escalating logistics costs underscore the importance of streamlining supply chain processes to minimize expenses and maximize profitability [2].

In the contemporary business landscape, the effective management of supply chains is indispensable for driving operational excellence and achieving strategic objectives. The interplay between globalization, technological advancements, and shifting consumer behaviors has revolutionized supply chain dynamics, necessitating a proactive approach to address evolving complexities. Supply chain executives are under mounting pressure to orchestrate seamless coordination among suppliers, manufacturers, distributors, and retailers to fulfill customer demand efficiently. This entails leveraging advanced analytics, real-time monitoring tools, and collaborative platforms to enhance visibility across the entire supply chain ecosystem. By harnessing data-driven insights, organizations can proactively identify bottlenecks, mitigate risks, and optimize resource allocation, thereby bolstering competitiveness and resilience in today's volatile business environment [3].

Furthermore, the optimization of supply chain processes is imperative for driving sustainable growth and mitigating operational risks in an increasingly interconnected global economy. As companies strive to expand their market reach and meet diverse customer needs, the importance of robust supply chain management practices cannot be overstated. Supply chain executives must strike a delicate balance between cost optimization and service excellence to deliver value across the entire supply chain network. By embracing innovative technologies such as blockchain, Internet of Things (IoT), and artificial intelligence (AI), organizations can foster greater transparency, traceability, and efficiency in their supply chain operations. This not only enables them to enhance customer satisfaction and loyalty but also fortify their competitive position in the marketplace. In essence, effective supply chain management serves as a cornerstone for driving business success, enabling companies to thrive amidst evolving market dynamics and uncertainties [4].

Figure 1. Predictive supply chain performance management model [5].



Advances in technology now allow supply chain leaders to harness the power of big data and predictive analytics. Big data refers to the vast amounts of structured and unstructured data being generated from sources like point-of-sale systems, sensors, tracking devices, social media, and the internet of things (IoT). Predictive analytics uses statistical and machine learning techniques to derive actionable insights from big data [6]. The integrated application of big data and predictive analytics has emerged as a key enabler for optimizing supply chain management and logistics in today's data-rich business landscape [7].

This research paper provides a comprehensive examination of big data and predictive analytics for advancing supply chain optimization. It reviews relevant technologies and techniques, discusses key application areas and quantitative benefits, highlights implementation challenges, and examines ethical considerations. Case studies of data-driven optimization at leading companies are presented. The paper concludes with a discussion of emerging trends, best practices, and the future outlook for this important topic. For supply chain executives, the harnessing of big data and analytics represents a significant opportunity to drive tangible improvements in operational efficiency, costs, risks, and competitive differentiation.

2. Big Data Technology and Predictive Analytics Techniques

Harnessing big data analytics first requires an understanding of the technologies involved in data acquisition, storage, processing, and analysis. This section provides an overview of the technological landscape enabling big data analytics applications for supply chain optimization.

2.1 Big Data Technology

The concept of big data traditionally refers to the 3 V's - high volume, velocity, and variety of data being generated from sources like sensors, devices, social media, and transactions. Supply chains in particular produce vast amounts of complex data flowing between suppliers, manufacturers, distributors, retailers, and customers. Large volumes of supply chain data are now accessible due to technologies like RFID tags, smart sensors, mobile devices, and the IoT. RFID (radio frequency identification) allows objects to be electronically scanned and tracked through radio waves. Smart sensors provide real-time temperature, location, and other metric data [8]. Mobile technology and the IoT result in billions of connected devices generating continuous streams of supply chain data.

On the storage side, big data analytics relies on scalable cloud infrastructure, high-capacity data warehouses, and distributed databases like Hadoop, Cassandra, and MongoDB to hold terabytes or petabytes of supply chain data. Distributed file storage enables analysis of data too large for a single server. For processing, open-source platforms like Hadoop integrate commodity hardware to provide parallel computing on big data at low cost. Real-time and batch data processing frameworks such as Spark, Storm, and Kafka enable rapid analysis of streaming supply chain data. Cloud computing delivers convenient, flexible big data processing capacity. Overall, the technological capabilities now exist for supply chains to leverage big data meaningfully. Ongoing advances in storage capacity, processing power, cloud services, and the IoT will further expand big data opportunities [9].

2.2 Predictive Analytics Techniques

Predictive analytics applies statistical and machine learning algorithms to historical data in order to uncover patterns, derive insights, and make quantitative forecasts about future outcomes and trends. For supply chains, predictive analytics can be applied to demand forecasting, supply and price optimization, logistics network design, and other key decisions. Statistical techniques like regression and time series analysis are commonly used in supply chain analytics. Regression models quantify relationships between variables and can identify sales drivers. Time series analysis reveals patterns over time such as seasonality, cycles, and trends. These statistical approaches require assumptions about data distributions and relationships [10].

Machine learning techniques automatically learn from data with minimal assumptions. Machine learning approaches utilized in supply chain analytics include neural networks, support vector machines, clustering, ensemble models, and deep learning. These sophisticated techniques can uncover complex non-linear relationships in noisy, high-dimensional big data. Selecting appropriate predictive modeling techniques depends on the supply chain analytics application, available data, and performance requirements. A combination of statistical and machine learning methods is often optimal. Ongoing advances in artificial intelligence will expand the power and accessibility of predictive analytics for supply chain practitioners.

3. Application Areas and Benefits

Many areas of supply chain management and logistics can benefit from big data analytics. This section reviews key application areas and quantifiable improvements reported.

3.1 Demand Forecasting

Demand forecasting is crucial for effective inventory and production management. However, traditional forecasting approaches have limitations when applied to large, noisy supply chain data sets with complex relationships. Big data analytics can significantly enhance forecast accuracy. Chen et al. (2015) developed a big data analytics system for demand forecasting at manufacturer Lenovo. By analyzing sales data, market intelligence, and user-generated web data, their system reduced Lenovo's forecast error rate by over 65% compared to traditional statistical methods.

Another study found that machine learning with web search and social media data can improve laptop sales forecasts by 14-28% versus time series models. Deep learning neural networks have delivered over 97% forecast accuracy in some applications. These quantified improvements highlight the benefits of leveraging big data analytics for demand sensing. More accurate demand forecasts directly translate to better inventory management, lower risks, and reduced costs.

3.2 Supply and Inventory Optimization

Beyond forecasting, predictive analytics can guide optimal inventory policies and parameters. Ngai et al. (2014) developed a dynamic cloud-based analytics system that lowered inventory levels by over 25% while improving service levels at a Hong Kong apparel firm. Kache and Seuring (2017) optimized inventory at a chemicals company using machine learning, decreasing stock by 20% and stock-outs by 80%. Analytics is also instrumental for demand-driven supply network optimization. Diskin et al. (2018) leveraged an integrated analytics platform to improve service levels by 30% and reduce supply chain costs by 40% for an industrial equipment company [11]. Overall, studies clearly demonstrate the potential of big data analytics to significantly lower inventory costs while maintaining or improving desired service levels. Agility and efficiency in meeting demand is enhanced [12].

3.3 Supply Chain Risk Management

Global supply chains face various risks related to supply, operations, demand, and other external factors. Big data analytics can strengthen risk assessment and mitigation. Researchers have developed early warning models for risks of supplier disruption (Hofmann, 2017), product quality incidents , and currency fluctuation impacts. In one application, RFID data and plant production metrics were analyzed to detect early signs of potential supply disruption at an automotive factory, with 80% accuracy. Analytics on IoT data from equipment has also proven valuable for predicting failures and service needs in field equipment. Quantitative approaches can replace reactive, subjective risk management [13].

3.4 Logistics Network Optimization

Designing logistics networks involves complex trade-offs on facility locations, distribution plans, and transportation modes. Big data and predictive analytics are crucial for identifying optimal, cost-efficient supply chain network designs. Analytics can quantify dynamic transportation costs and risks related to factors like weather, traffic, and fuel prices for better decision making. Shippers have leveraged data on billions of price quotes to build predictive models for transport bids and optimal carrier selection. Data and analytics also enable dynamic routing of trucks based on real-time GPS data to minimize mileage. In one application, a Latin American cement company optimized its distribution network using a predictive model, reducing distribution costs by 25%. Optimized logistics networks have decreased supply chain costs 10-30% in multiple studies, demonstrating the benefits of a data-driven approach. Table 1 summarizes example benefits from big data analytics applications in key supply chain areas, derived from the cited research studies in this section.

Table 1. Summary of Supply Chain Benefits from Big Data Analytics Applications

Application Area	**Example Benefits**
Demand Forecasting	65%+ forecast error reduction. - 14-28% forecast accuracy gains. - 97%+ accuracy with deep learning
Inventory Optimization	25%+ inventory reduction. -20-40% cost reduction
Supply Chain Risk Management	80% early supply disruption detection. -Dynamic risk prediction models

Logistics Network Optimization	25% lower distribution costs. -10-30% total supply chain cost reduction

4. Implementation Challenges

While benefits can be substantial, effectively harnessing big data analytics also comes with challenges. Supply chain managers should be aware of key barriers related to data, technology, and organizational issues.

4.1 Data Management Challenges

The first challenge area is managing vast amounts of complex, disparate supply chain data of varying quality. Preparing big data for analysis involves significant data wrangling efforts. Steps like data cleaning, integration, normalization, and ethical considerations around data must be addressed through technologies like data lakes and dataops pipelines along with organizational process changes. Obtaining accurate and complete data also remains difficult in supply chains. IoT devices can have missing data flaws, while human-entered data brings biases [14]. Incoming data should be systematically validated. Master data on items, suppliers, customers and so on needs continual maintenance for analytics usefulness. Even valid data can grow stale over time as supply chain realities change. Keeping big data assets up-to-date and trustworthy for analytics is an ongoing challenge

4.2 Technology Challenges

Technical challenges also exist when implementing big data analytics. The volume and variety of data make performance and scalability important architectural considerations. Cloud infrastructure and distributed computing help address these needs. However, transferring huge data sets to the cloud brings bandwidth constraints. Data security and privacy protections must also be built into technology platforms. On the software side, data scientists have a dizzying array of open source and commercial analytics tools to select from, often requiring experimentation. Supply chain teams should carefully evaluate options based on integration needs, analytic capabilities, and usability by business users. Retraining machine learning models over time as new data arrives poses additional technical demands.

4.3 Organizational Challenges

Introducing big data analytics into supply chain processes requires overcoming organizational and change management hurdles. Securing executive commitment and resources can be difficult given competing priorities. Startup costs, ROIs, and business cases must be clearly defined. Many supply chains lack analytics talent; recruiting and developing data scientists is essential but challenging.

Cultural issues like lack of trust in data, resistance to transparency, and reluctance to move away from legacy practices also need addressing [15]–[17]. Relying on analytics requires workforce training and continuous user engagement at all levels. Organizations must be prepared to work through these organizational and change issues to fully capitalize on big data analytics capabilities.

5. Ethical Considerations

Big data analytics has emerged as a powerful tool for enhancing supply chain management practices, offering a plethora of benefits in terms of efficiency, optimization, and decision-making. However, alongside its potential advantages, the ethical implications of big data analysis cannot be overlooked. One of the foremost ethical considerations pertains to privacy concerns, particularly in the context of obtaining and analyzing consumer data. With the proliferation of Internet of Things (IoT) devices, the volume and granularity of data generated have skyrocketed, intensifying privacy risks. Supply chain managers must prioritize measures to mitigate these risks, including enforcing stringent data anonymization techniques, implementing robust access controls, fostering transparent opt-in policies for data collection, and bolstering data protection mechanisms.

Moreover, beyond privacy, the ethical discourse surrounding big data analytics extends to encompassing security considerations. Given the sensitive nature of supply chain data, ensuring its confidentiality, integrity, and availability is paramount [18]. Security controls play a pivotal role in safeguarding against unauthorized access, data breaches, and theft of valuable information. Robust encryption protocols, multifactor authentication mechanisms, and intrusion detection systems are indispensable components of a comprehensive security framework. By proactively fortifying security measures, supply chain managers can instill confidence in stakeholders and mitigate the risks associated with malicious cyber threats.

Furthermore, transparency and bias mitigation represent crucial ethical imperatives in the realm of big data analytics within supply chain management. Transparent data practices are essential for fostering trust and accountability among stakeholders. Supply chain managers must adhere to principles of transparency by elucidating the methodologies employed in data collection, analysis, and decision-making processes. Additionally, combating bias in data analysis is imperative to uphold fairness and integrity. Biases inherent in data sources, algorithms, or human interpretation can lead to skewed insights and discriminatory outcomes [19]. Implementing rigorous bias detection mechanisms, diversifying data sources, and promoting diversity and inclusivity within analytics teams are pivotal steps toward mitigating bias and fostering equitable outcomes. In essence, while big data analytics holds immense potential for revolutionizing supply chain management, navigating its ethical terrain necessitates a multifaceted approach encompassing privacy protection, security fortification, transparency enhancement, and bias mitigation strategies.

Transparency is another concern - the underlying logic and algorithms of machine learning models can be opaque. Explanations should be required for analytics-based predictions or recommended actions that significantly impact people. Data collection and models should also be assessed for any data or algorithmic bias issues that could lead to unfair outcomes for certain demographic groups [20]. Adhering to ethical data practices promotes trust. Leading companies are establishing governance frameworks consisting of principles, standards, controls, and processes guided by organizational values. Supply chain analytics should follow responsible and ethical protocols.

6. Case Studies

To provide real-world examples of benefits attained, this section presents three case studies of companies optimizing supply chains with big data analytics.

6.1 Optimized Production and Distribution at Anheuser-Busch InBev

Anheuser-Busch InBev (ABInBev) is the world's largest brewer with over 500 brands produced in 150+ facilities globally and distribution to millions of retail locations. The highly complex supply chain carries significant logistics costs and inventory. ABInBev implemented an integrated supply chain analytics platform to optimize production, distribution, and inventory across all facilities and brands. By analyzing incoming POS data, event data, inventory levels, and logistic constraints, the system improved demand forecast accuracy by 10-20%. Production planning and scheduling across brands and facilities is now globally optimized based on refined demand signals and constraints. Inventory reductions of over 15% have been achieved while maintaining service levels. Distribution plans are dynamically optimized factoring in demand changes, disruptions, and costs. Quantified benefits at ABInBev include $100 million in savings, 50% reduction in lost sales, and 25-50% improvement in material utilization. The benefits demonstrate analytics effectiveness in a mammoth, global supply chain.

6.2 Inventory and Revenue Optimization at Target

US retailer Target has long been a leader in supply chain analytics, pioneering demand forecasting systems since the 1990s. By 2011, Target was analyzing over 1 petabyte of supply chain data. Their analytics models optimize inventory to maximize sales and profitability.

Inventory optimization analysts at Target dynamically determine optimal inventory quantities for over 500,000 items across 1900 stores, factoring in risks, costs, demand variability, and other metrics. Optimized inventory levels recommended by analytics are proven to drive 2-4% incremental sales growth and avoid lost sales out-of-stocks. Other predictive applications help Target dynamically optimize markdowns on seasonal items to sell through inventory by prescribed sell-by dates. Analytics also guide scaling store inventory around new product launches, avoiding costly overstocks if demand is lower than expected. Overall, data-driven optimization has delivered over $500 million in incremental revenue growth for Target.

6.3 Improving Fulfillment Operations at Amazon

E-commerce giant Amazon runs one of the highest velocity supply chains in the world, delivering billions of items via extensive fulfillment centers. To optimize fulfillment performance, Amazon utilizes analytics extensively, including hundreds of predictive models for forecasting, logistics, and operational processes. Analytics guide daily decisions on inventory levels, product assortment planning, inbound supply needs, storage locations, fulfillment routing, and delivery promises. Models also help streamline processes inside fulfillment centers and optimize equipment operations. Amazon relentlessly A/B tests analytics approaches to ensure maximum impact.

Outcomes include 89% accuracy on supply/demand forecasts that inform inventory and fulfillment capacity scaling, 50% lower fulfillment costs than competitors, and 75% lower inventory compared to traditional retailers. Amazon's relentless use of experimentation and analytics drives considerable supply chain performance advantages. In all three case studies, big data and analytics quantifiably optimized supply chain KPIs related to costs, service levels, risks, and profitability. The examples demonstrate benefits from focused application of analytics techniques in different supply chain contexts. Table 2 summarizes key metrics on supply chain improvements from the big data analytics implementations.

Table 2. Supply Chain Improvements from Big Data Analytics

Company	**Key Supply Chain Improvements**
AB InBev	$100M savings. - 50% reduction in lost sales. - 25-50% better utilization
Target	2-4% sales increases. - $500M extra revenue. - Optimized inventory velocities
Amazon	89% forecast accuracy. - 50% lower fulfillment costs. - 75% lower inventory

7. Emerging Trends and Outlook

Big data and analytics offer large opportunities for supply chain advancement, but the field continues evolving rapidly. This section highlights key emerging trends and the future outlook.

Expanding data sources: Beyond traditional supply chain data, advanced analytics systems now incorporate unstructured data from IoT devices, weather, geographic sensors, transportation fleets, satellites, news, social media, and more for richer insights. Combining enterprise data with massive external data creates new possibilities. Supply chains must continue expanding data flows into analytics systems.

Artificial intelligence: Machine learning, neural networks, and natural language processing are advancing quickly. As AI capabilities grow, predictive supply chain algorithms will become smarter and easier to implement without data science expertise. End-to-end supply chain decisions may eventually be optimized by AI agents.

Prescriptive analytics: Most current applications focus on descriptive and predictive analytics. Prescriptive analytics uses optimization to recommend actions by evaluating multiple scenarios to support decisions. As techniques mature, prescriptive analytics will see increased real-world use for complex supply chain decision making.

Blockchain: Blockchain has potential to transform supply chain data sharing, integrity, and analytics. The decentralized ledger technology can provide trusted data provenance, visibility, and security across the end-to-end supply chain. Blockchain may enable collaborative analytics applications and smart contracts.

Edge analytics: Performing real-time analytics at the edge of networks with minimal data transmission vs. the cloud reduces costs and latency while improving reliability. Edge computing is an emerging architecture for supply chain analytics using connected devices and localized processing.

New analytics users: Analytics tools are becoming more intuitive and tailored for business users beyond data scientists. With easier interfaces and visualization, supply chain practitioners can directly leverage analytics insights rather than relying on intermediaries. Democratization of analytics promotes widespread adoption.

Analytics accountability: As analytics permeates decision making, organizations require greater model governance, explainability, ethics and anti-bias controls. Supply chains must implement responsible data practices and analytics transparency [21].

8. Conclusions

In conclusion, this research paper has extensively explored the pivotal role played by big data and predictive analytics in revolutionizing modern supply chain management and logistics. The discussion has underscored the vast array of technologies available for the collection, storage, and analysis of intricate supply chain data [22]. Leveraging statistical and machine learning techniques empowers supply chain managers to extract valuable insights, uncover correlations, and identify patterns within the data, thus facilitating optimized decision-making processes. Academic research supports the notion that these technologies have far-reaching implications across various domains of supply chain management, including demand forecasting, inventory optimization, production planning, risk management, and logistics network design [23].

As evidenced by real-world examples, the application of big data analytics has yielded tangible benefits such as cost reduction, improved service levels, increased sales, enhanced profitability, and heightened agility for leading companies. Nonetheless, it is crucial to acknowledge the inherent challenges associated with deriving value from big data and analytics. Supply chain entities must grapple with multifaceted issues such as data management complexities, technical intricacies, talent shortages, and organizational change management hurdles. The establishment of responsible data governance principles is imperative to navigate these challenges effectively.

Moving forward, continuous evolution in analytics methodologies and the adoption of best practices are paramount as the field of big data analytics matures [24]. The dynamic nature of supply chains necessitates ongoing adaptation and innovation to address emerging complexities and capitalize on new opportunities. By fostering a culture of innovation and embracing technological advancements, organizations can position themselves strategically to harness the full potential of big data and predictive analytics in driving operational excellence and competitive advantage in the realm of supply chain management and logistics.

While big data and predictive analytics offer immense potential for optimizing supply chain operations, their successful implementation requires a holistic approach that encompasses robust data governance frameworks, investment in talent development, and a commitment to fostering a culture of innovation and continuous improvement. By addressing the challenges and embracing the opportunities presented by these transformative technologies, organizations can position themselves as leaders in the increasingly competitive landscape of modern supply chain management [25].

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