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Data Analytics Techniques in Supply Chain Management: A Systematic Review of Models, Applications, and Research Directions

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ABSTRACT

This review investigates the role of data analytics in supply chain management (SCM), synthesizing findings from 92 peer-reviewed articles publishe between 2010 to 2024. A structured taxonomy is presented, classifying analytics into six types: descriptive, diagnostic, predictive, prescriptive, real-time/streaming, and hybrid lifecycle analytics. These are mapped to key SCM functions such as demand forecasting, inventory management, logistics optimization, and supplier assessment. The analysis highlights the growing adoption of predictive and prescriptive models, while noting that descriptive tools remain dominant in practice. Key gaps include limited empirical validation, underutilization of advanced analytics in SMEs, and lack of cross-functional integration. Emerging trends include hybrid AI models, real-time decision systems, and sustainability-focused analytics. This study contributes a unified framework for understanding and deploying analytics in SCM, and outlines directions for future research in areas such as digital twins, analytics democratization, and multi-tier collaboration.

Keywords: supply chain analytics, predictive modeling, prescriptive analytics, logistics

INTRODUCTION

In today's globally interconnected and competitive markets, supply chains have become increasingly complex, dynamic, and vulnerable to disruptions. The growing need for agility, responsiveness, and efficiency has compelled organizations to shift from traditional decision-making toward more data-centric models. With the proliferation of digital technologies and the increasing availability of structured and unstructured data, data analytics has emerged as a cornerstone of modern supply chain management (SCM).

Data analytics in SCM involves the application of analytical tools and techniques to derive actionable insights from data. These insights support critical decisions across procurement, inventory management, production planning, distribution, and customer service [1]. By identifying patterns, predicting outcomes, and recommending optimal actions, data analytics empowers organizations to optimize operations and enhance competitiveness in increasingly volatile and data-driven environments [1].

The evolution of analytics in SCM has followed a progressive trajectory—transitioning from historical reporting to real-time and predictive modeling. Three core analytics paradigms are widely recognized: descriptive, predictive, and prescriptive analytics. Descriptive analytics focuses on summarizing past performance, predictive analytics forecasts future events, and prescriptive analytics suggests optimal decision paths based on data models [2]. The integration of real-time analytics—enabled by technologies such as the Internet of Things (IoT), sensors, and GPS—now allows firms to monitor supply chain operations continuously, increasing visibility and decision speed [3].

Empirical and theoretical studies have consistently demonstrated that the integration of analytics in supply chains enhances key performance indicators such as inventory turnover, forecast accuracy, service levels, and operational agility [4][5]. Predictive analytics, in particular, facilitates proactive risk management and accurate demand forecasting, while prescriptive analytics contributes to optimizing resource allocation, production schedules, and logistics planning [6].

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EVOLUTION OF ANALYTICS IN SCM

Historically, supply chain decisions were made using rule-of-thumb techniques, static models, or limited spreadsheet-based tools. Early 2000s business intelligence systems brought descriptive insights through dashboards and KPI monitoring. However, recent advancements have shifted the paradigm toward more advanced analytics capable of handling higher data volumes, unstructured data types, and real-time decision needs.

As Waller and Fawcett highlight, the convergence of data science, predictive analytics, and automated decision systems is fundamentally reshaping how supply chains are designed and managed [7]. Rather than simply reacting to changes, modern supply chains can now anticipate disruptions and adapt in near real-time—supported by integrated analytics platforms and cloud-based decision architectures.

Nguyen et al. [8] propose a three-part taxonomy that classifies analytics in SCM into (i) descriptive models for pattern recognition, (ii) predictive models using statistical and machine learning algorithms, and (iii) prescriptive models leveraging optimization, simulation, and heuristics. This classification is increasingly used in both academic literature and industry applications to guide analytics adoption strategies.

ROLE OF ANALYTICS ACROSS SCM FUNCTIONS

Data analytics plays a transformative role across various supply chain functions. In demand forecasting, predictive models such as regression analysis, time-series forecasting (e.g., ARIMA), and machine learning algorithms (e.g., decision trees, neural networks) are used to anticipate customer demand. These models enable firms to align procurement and production with expected market trends, thereby reducing overstocking and stockouts [9].

In inventory management, descriptive analytics tools help track inventory flows, identify shrinkage, and optimize reorder points. Traditional methods like Economic Order Quantity (EOQ) models are enhanced by analytics dashboards and simulation tools, offering data-driven insights into inventory turnover and safety stock levels [1].

Logistics and transportation functions benefit significantly from prescriptive analytics, which enables route optimization, fleet scheduling, and delivery performance tracking. Algorithms such as mixed-integer linear programming and metaheuristics help reduce transportation costs and improve delivery timelines [10]. Real-time tracking systems integrated with analytics platforms now provide live visibility into fleet operations and warehouse movements.

In supplier analytics, firms use scorecards, dashboards, and predictive models to evaluate supplier performance, monitor compliance, and assess risk exposure. Event-based monitoring allows organizations to detect early signs of supplier distress, enabling proactive mitigation strategies [11].

Additionally, event-driven analytics—powered by RFID, IoT, and sensor networks—enables the development of supply chain "control towers" that provide continuous visibility into end-to-end operations. These systems allow supply chain professionals to respond to disruptions in real time, such as delays, bottlenecks, or quality issues [3].

Empirical Evidence and Industry Impact

Fosso Wamba and Gunasekaran [5] provide empirical validation for the performance gains associated with analytics adoption in SCM. Their research shows measurable improvements in customer service, operational efficiency, and strategic agility. Maheshwari et al. [6] further highlight that firms deploying prescriptive and predictive analytics experience substantial benefits in terms of reduced lead times, improved forecast accuracy, and enhanced coordination across supply chain partners.

Nevertheless, several barriers still hinder the widespread implementation of data analytics in SCM. These include fragmented data systems, insufficient analytical skills among supply chain personnel, high implementation costs, and resistance to change in traditional organizations. To overcome these barriers, firms are investing in training, cloud analytics platforms, and cross-functional integration efforts.

Collaborations between academia and industry are also emerging to co-develop scalable, industry-ready analytics solutions. Future innovations such as digital twins, edge computing, and AI-assisted decision systems are expected to further enhance the capabilities of analytics in SCM [12].

RATIONALE FOR THIS REVIEW

Despite increasing academic interest, the literature on data analytics in SCM remains fragmented. Many existing reviews focus narrowly on specific technologies (e.g., big data, machine learning) or particular functional domains (e.g., logistics), lacking a holistic view of analytics techniques applied across the entire supply chain [8][9].

This review aims to fill this gap by systematically categorizing the range of data analytics techniques used in SCM, mapping these techniques to their application areas, and identifying current challenges and future research opportunities. It contributes to both academic and practical discourse by offering a comprehensive synthesis of the current landscape of supply chain analytics.

METHODOLOGY

This review adopts a semi-systematic literature review approach to identify, analyze, and classify the various data analytics techniques applied in supply chain management (SCM). The methodology combines structured database searches with manual reference tracking to ensure comprehensive coverage of peer-reviewed academic literature. This section details the search strategy, selection criteria, and analytical framework used in the review process.

Research Objectives

The objectives of this review are:

- To identify and categorize the data analytics techniques currently used in SCM.
- To map these techniques to specific supply chain functions (e.g., procurement, logistics, inventory management).
- To analyze trends, gaps, and future research directions in analytics-driven SCM practices.

Literature Search Strategy

A structured search was conducted across three major academic databases commonly indexed in Scopus:

- ScienceDirect
- IEEE Xplore
- SpringerLink
- Emerald Insight (for logistics/SCM journals)
- Google Scholar (for supplementary grey literature)

The following search terms were used (with Boolean operators):

"data analytics" OR "predictive analytics" OR "descriptive analytics" OR "prescriptive analytics" OR "machine learning") AND ("supply chain management" OR "logistics" OR "procurement" OR "inventory" OR "forecasting"

Searches were limited to peer-reviewed journal articles and conference proceedings published between 2010 to 2024.

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Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Subject Focus	Data analytics techniques applied in SCM	Articles not related to SCM or analytics
Publication Type	Peer-reviewed journal articles, conference papers	Editorials, blogs, theses, book reviews
Language	English	Non-English publications
Time Frame	2010–2024	Publications prior to 2010
Methodological Rigor	Studies applying or reviewing analytical models or techniques	Theoretical papers without analytics focus

TAXONOMY OF DATA ANALYTICS IN SCM

This section presents a structured taxonomy of data analytics techniques applied in supply chain management (SCM), categorized by analytical type and mapped to key functional areas within the supply chain. The taxonomy draws upon a synthesis of current literature and is structured around four core dimensions: descriptive, diagnostic, predictive, and prescriptive analytics. Each dimension represents a maturity level in the analytics continuum, supporting increasingly advanced forms of decision-making.

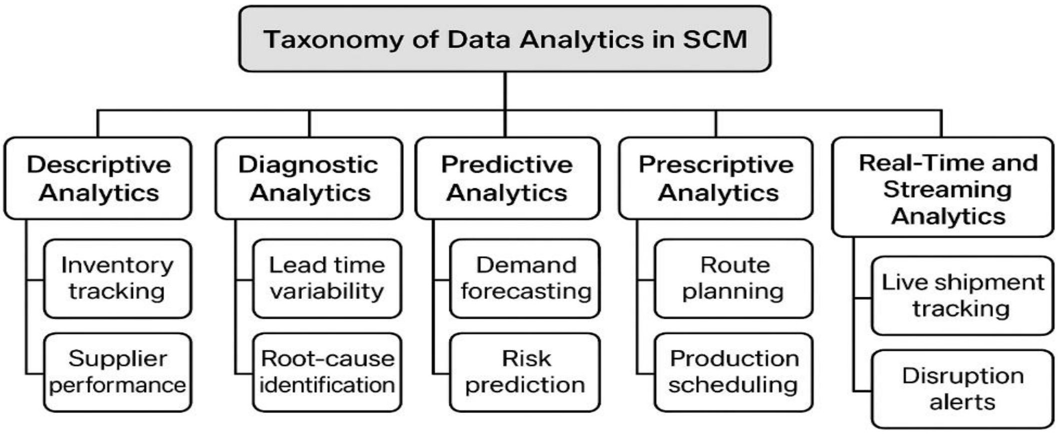

Figure 1. Taxonomy of Data Analytics

Descriptive Analytics

Descriptive analytics provides foundational insights into past supply chain activities by summarizing historical data through visualization, dashboards, and key performance indicators (KPIs). It serves as the basis for monitoring supply chain processes and identifying inefficiencies or anomalies. Common tools in this category include enterprise resource planning (ERP) systems, data warehousing, and business intelligence (BI) platforms [13]. These systems capture and aggregate large volumes of transactional and operational data to aid in real-time visibility and performance reporting. Descriptive analytics has been widely used for demand tracking, order status monitoring, and supplier scorecarding [14]. For instance, track-and-trace systems in logistics are widely used to improve transparency and monitor shipment flows across global networks [15].

Diagnostic Analytics

Diagnostic analytics explores relationships between variables to understand the root causes of supply chain performance fluctuations. Unlike descriptive analytics, which focuses on "what happened," diagnostic analytics

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addresses "why it happened." Tools such as OLAP (Online Analytical Processing), drill-down dashboards, and data mining algorithms are employed for this purpose [16]. Supply chain managers use these techniques to investigate issues like fluctuating lead times, recurring bottlenecks, and stockouts. Kamble et al. [17] demonstrated how data mining techniques can support diagnostics in warehousing, enabling analysis of inventory inaccuracy or unbalanced picking frequencies.

Predictive Analytics

Predictive analytics leverages historical data, statistical modeling, and machine learning algorithms to forecast future outcomes. In SCM, predictive tools are primarily used for demand forecasting, risk assessment, supplier reliability prediction, and inventory optimization [18]. Common methods include time-series forecasting (e.g., ARIMA, exponential smoothing), regression models, decision trees, support vector machines (SVM), and neural networks [19]. These models provide companies with foresight to better align supply and demand, optimize resource allocation, and anticipate disruptions. Waller and Fawcett [20] described predictive analytics as a "revolution" in supply chain design, enabling real-time anticipation of variability and system behaviors across interconnected nodes.

Prescriptive Analytics

Prescriptive analytics goes a step further by recommending optimal decisions using mathematical models and simulations. It is most commonly applied in route optimization, production scheduling, network design, and inventory control policies [21]. Prescriptive models include linear programming, integer programming, genetic algorithms, simulation models, and multi-objective optimization frameworks [22]. These methods are embedded into advanced planning systems (APS) and are often used in scenario planning.

Amiri [23] proposed an efficient optimization-based model for distribution network design, while Dekker et al. [24] demonstrated how operations research models support green logistics by minimizing emissions and fuel use.

Real-Time and Streaming Analytics

Recent advances in IoT and sensor technologies have enabled real-time data capture and streaming analytics. These analytics allow supply chain managers to respond to disruptions immediately and optimize decisions continuously [25].

Examples include RFID-based tracking, cloud-integrated transport monitoring, and control tower dashboards that consolidate data from across global operations. Jakobs et al. [15] illustrate how real-time event processing enhances transportation control and proactive alerting systems.

Hybrid and Lifecycle Analytics

Kao et al. [26] introduce the concept of supply chain lifecycle decision analytics, which integrates all analytics types across strategic, tactical, and operational stages. This comprehensive approach enables lifecycle-aware decisions, such as capacity planning during design, demand sensing during operations, and sustainability tracking post-delivery.

Additionally, hybrid analytics frameworks combining machine learning with optimization have been proposed for multi-objective problems in volatile environments [27].

Table 2. Analytics Types and Applications in SCM

Analytics Type	Primary Techniques	SCM Application Areas	Key References
Descriptive	Dashboards, BI, Data Warehousing	Inventory tracking, supplier performance	[13][14][15]
Diagnostic	OLAP, Data Mining, Drill-down Analysis	Lead time variability, root-cause identification	[16][17]
Predictive	Regression, ML, Forecasting, Neural Networks	Demand forecasting, risk prediction	[18][19][20]

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Prescriptive	LP, ILP, Genetic Algorithms, Simulation	Route planning, scheduling, network optimization	[21][22][23][24]
Real-Time/Streaming	IoT, Event Processing, RFID, Control Towers	Live shipment tracking, disruption alerts	[15][25]
Lifecycle/Hybrid	Combined Predictive + Optimization Models	End-to-end SCM decision support	[26][27]

DISCUSSION

This systematic review has consolidated and categorized data analytics techniques into six core types-descriptive, diagnostic, predictive, prescriptive, real-time/streaming, and lifecycle/hybrid analytics-highlighting their strategic applications across the supply chain. From the analysis, it is evident that data analytics is no longer a supporting function but a central enabler of supply chain performance, adaptability, and strategic foresight.

Integration of Analytics across Supply Chain Functions

The taxonomy confirms that different analytics types are aligned with specific functions across the supply chain. Descriptive and diagnostic analytics provide foundational visibility through dashboards and data mining, supporting real-time reporting and operational awareness [13][14][16]. However, these approaches primarily offer retrospective insights, limiting their ability to guide proactive decision-making.

Predictive analytics plays a critical role in demand forecasting, risk mitigation, and supply planning, offering organizations the capability to anticipate variability and align resources proactively [18][19][20]. Meanwhile, prescriptive analytics is increasingly used in route optimization, production scheduling, and network design—offering prescriptive pathways using optimization algorithms, heuristics, and simulation models [21][22][23].

The emergence of real-time and streaming analytics, enabled by IoT and RFID technologies, allows for continuous operational monitoring and responsive intervention, especially in logistics and transport [15][25]. This capability is particularly valuable in global supply chains, where disruptions can cascade quickly. Additionally, hybrid lifecycle analytics, which combine multiple analytical models across the strategic-to-operational spectrum, reflect a maturing approach to holistic decision support in SCM [26][27].

Gaps in Research and Industry Practice

Despite clear advancements, the review identifies several persistent gaps:

- Siloed Analytics Use: Many organizations implement analytics in isolated domains (e.g., demand forecasting or fleet management) rather than as an integrated, end-to-end solution. This restricts the realization of full supply chain visibility and coordinated optimization [14][17].
- Limited Empirical Validation: A considerable number of academic studies rely on synthetic datasets or theoretical models, with few grounded in longitudinal or multi-tier empirical data. This limits the generalizability and practical transferability of proposed models [18][20].
- Technology-Readiness Divide: While large corporations adopt advanced analytics platforms, small and medium enterprises (SMEs) often face adoption barriers due to cost, skill shortages, and data fragmentation [16][19].
- Underutilized Prescriptive Models: Compared to predictive models, prescriptive analytics remains underrepresented in practice, particularly in inventory optimization, supplier allocation, and multi-echelon planning. Its deployment often requires mature data infrastructure and analytical literacy that many firms lack [21][23].

Methodological Trends and Observations

The literature reviewed reveals a dominance of hybrid models integrating machine learning, simulation, and optimization methods. This shift reflects a growing awareness of complex interdependencies in SCM and the need for dynamic modeling under uncertainty [26][27].

Another methodological trend is the application of event-driven analytics and control towers for continuous monitoring. These systems support not only exception management but also real-time analytics for logistics visibility and production bottleneck resolution [15][25]. However, scalability and standardization of such systems remain research challenges.

The review also notes that metrics used to evaluate analytics effectiveness are inconsistent. Few studies employ standardized KPIs such as order cycle time, perfect order rate, or inventory turns. Future research should adopt benchmark-driven evaluation frameworks to improve comparability and practitioner relevance.

CONCLUSION

This systematic review has examined the landscape of data analytics techniques in supply chain management (SCM), offering a structured taxonomy that includes descriptive, diagnostic, predictive, prescriptive, real-time/streaming, and lifecycle/hybrid analytics. These categories reflect the maturity continuum of analytics capabilities, from retrospective data interpretation to proactive and prescriptive decision-making.

The findings confirm that data analytics is increasingly embedded across all major SCM functions—such as demand forecasting, inventory management, logistics optimization, and supplier risk evaluation. Organizations adopting predictive and prescriptive analytics report improved operational efficiency, enhanced responsiveness, and greater supply chain resilience. Real-time analytics, enabled by IoT and cloud computing, is driving event-driven decision models, further increasing visibility and agility.

Despite these advances, several challenges persist. These include fragmented data systems, limited analytical capabilities among supply chain personnel, underutilization of advanced techniques such as prescriptive modeling, and uneven adoption across organizational sizes. The review also identified a gap in empirical validation, with many studies relying on theoretical or simulated data. As such, further research is needed to explore cross-functional integration of analytics, implementation in small and medium enterprises (SMEs), and benchmark-driven performance assessments.

From a practical standpoint, this review provides managers with a framework for evaluating and deploying analytics tools in alignment with their strategic objectives and operational priorities. A phased analytics adoption approach—starting from descriptive insights and advancing toward predictive and prescriptive capabilities—can help firms build analytical maturity in a structured manner.

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