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(Review Article)

Autonomous inventory Intelligence: ML-driven predictive and prescriptive analytics for supply chain optimization

Shikha Duttyal *

Northern Illinois University, USA.

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Abstract

Artificial intelligence and machine learning technologies have transformed supply chain management through the integration of predictive demand forecasting with prescriptive inventory optimization. Modern ML algorithms process diverse data streams—from historical sales and promotions to external factors like weather patterns and market trends—to generate significantly more accurate demand predictions than conventional methods. Building on these forecasts, prescriptive analytics dynamically optimize inventory parameters across multi-echelon supply chains, simulating scenarios to balance service levels against holding costs. These integrated systems enable real-time automation of procurement decisions with continuous model refinement through feedback loops. Implementations across retail, manufacturing, and logistics sectors demonstrate substantial improvements in operational metrics, with various platforms offering distinctive capabilities for specific industry contexts. The evaluation of performance outcomes identifies key integration challenges with existing ERP ecosystems while highlighting operational resilience benefits in dynamic global markets. The transition toward autonomous supply chain management represents a fundamental advancement in operational capability that addresses contemporary volatility in global supply networks.

Keywords: Machine Learning; Supply Chain Optimization; Demand Forecasting; Prescriptive Analytics; Inventory Management

1. Introduction to ML and AI in Supply Chain Management

Supply chain management has undergone a dramatic transformation over the past decade, moving from traditional forecasting techniques based on historical averages and simple statistical models to sophisticated artificial intelligence and machine learning approaches. These advanced computational methods have enabled organizations to develop more responsive, data-driven, and autonomous operations that can adapt to rapidly changing market conditions [1]. The evolution marks a significant paradigm shift in how businesses approach demand planning and inventory control.

1.1. Evolution from Traditional Forecasting to AI-Powered Methods

The journey from conventional forecasting approaches to AI-powered methods represents a fundamental transformation in supply chain planning paradigms. Traditional methods relied heavily on historical data patterns and simple trend extrapolation, often failing to account for complex market dynamics and external variables. The introduction of machine learning algorithms has enabled systems to identify intricate patterns from vast datasets, incorporating both structured and unstructured data sources to generate significantly more accurate predictions. This technological evolution has shifted forecasting from a primarily reactive process to a proactive capability that can anticipate market changes before they materialize [1].

* Corresponding author: Shikha Duttyal.

1.2. The Growing Importance of Predictive and Prescriptive Analytics

Predictive analytics—which forecasts future demand patterns—and prescriptive analytics—which recommends specific actions to optimize outcomes—have emerged as complementary capabilities driving this transformation. These dual analytical approaches form the cornerstone of next-generation supply chain systems by bridging the gap between passive data analysis and autonomous decision-making [2]. This integration allows organizations to not only anticipate future demand with greater precision but also automatically implement optimal inventory strategies in response. As supply chains become increasingly complex and globalized, the ability to leverage these advanced analytics approaches has become a critical differentiator in maintaining competitive advantage.

1.3. Current Market Adoption Rates Across Industries

The adoption of AI and ML technologies in supply chain management varies considerably across industry sectors. Retail and e-commerce organizations have generally led implementation efforts, with manufacturing, consumer packaged goods, and logistics providers following closely behind. Technology-intensive industries demonstrate higher maturity levels in AI adoption, though implementation remains uneven across regions and organizational sizes [2]. Companies with existing digital infrastructure tend to achieve faster integration and greater benefits from these advanced analytics capabilities [1]. This variability in adoption reflects differences in digital readiness, organizational capabilities, and industry-specific supply chain challenges.

1.4. Research Objectives and Scope of the Study

This research aims to examine the technological frameworks enabling ML-based demand forecasting and AI-driven inventory optimization, evaluate their practical implementation across diverse industry contexts, and assess their impact on key performance indicators. The scope encompasses both the technical architecture of these systems—including data integration approaches, model selection, and system integration patterns—and the organizational considerations related to implementation, change management, and return on investment. By investigating both the technological and operational dimensions, this study seeks to provide a comprehensive understanding of how predictive and prescriptive analytics are transforming supply chain management practices in contemporary business environments.

2. Data Integration and ML-Based Demand Forecasting Models

The efficacy of machine learning approaches in demand forecasting hinges significantly on the breadth and quality of data integrated into predictive models. Modern forecasting systems transcend traditional reliance on historical sales data by incorporating a diverse array of information sources that collectively provide a more comprehensive view of demand drivers and market dynamics.

2.1. Structured and Unstructured Data Sources for Forecasting

Contemporary demand forecasting systems leverage an expansive range of data sources that extend far beyond conventional sales histories. Structured data elements include point-of-sale transactions, inventory positions, pricing information, promotion calendars, and order histories. These are complemented by unstructured and semi-structured data sources such as social media sentiment, competitor actions, web traffic patterns, and customer reviews. Additionally, external factors including macroeconomic indicators, weather forecasts, holiday calendars, and seasonal trends contribute valuable contextual information. The integration of these diverse data streams enables forecasting systems to develop a multidimensional understanding of demand patterns and their underlying drivers [3]. As noted in recent research, the ability to synthesize these varied information sources represents a fundamental advantage of ML-based approaches over traditional statistical methods, which typically accommodate a more limited range of variables.

2.2. Time-Series Models, Regression Analysis, and Deep Learning Approaches

The evolution of demand forecasting methodologies has progressed through several generations of increasingly sophisticated models. Traditional time-series approaches such as ARIMA (Autoregressive Integrated Moving Average) and exponential smoothing continue to serve as foundational techniques, particularly for stable products with clear seasonality patterns. More advanced regression models, including multiple linear regression and random forests, excel at incorporating external variables and identifying non-linear relationships between predictors and demand outcomes. The emergence of deep learning approaches—particularly recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and transformer models—has further enhanced forecasting capabilities by capturing complex temporal dependencies and long-range patterns that elude simpler models [4]. These neural network architectures demonstrate particular efficacy for products with irregular demand patterns, new product introductions, and forecast scenarios involving numerous exogenous variables.

Table 1 Comparison of Forecasting Methodologies [3, 4]

Methodology	Data Handling	Adaptability	Interpretability	Ideal Applications
Traditional Statistical	Limited, structured	Manual adjustment	High transparency	Stable demand patterns
Machine Learning	Multiple variables	Semi-automated	Moderate	Promotional and seasonal items
Deep Learning	Diverse data streams	Continuous learning	Limited ("black box")	Complex, high-volume patterns

2.3. Comparative Assessment of Model Accuracy and Adaptability

Research comparing various forecasting methodologies reveals nuanced performance differences across different product categories, demand patterns, and forecast horizons. Traditional statistical methods generally perform adequately for stable products with consistent demand patterns but struggle with intermittent demand, promotional impacts, and external disruptions. Machine learning approaches demonstrate superior adaptability in volatile market conditions and excel at capturing complex interactions between variables [3]. Deep learning models, while computationally intensive, show particular strength in scenarios with abundant historical data and complex seasonality patterns. However, their "black box" nature can present interpretation challenges for business stakeholders. Recent hybrid approaches that combine statistical foundations with machine learning enhancements have gained traction by balancing interpretability with adaptive performance. The selection of appropriate methodologies increasingly depends on specific business contexts, data availability, and the particular forecasting challenges faced by each organization [4].

2.4. Case Studies Highlighting Forecast Accuracy Improvements

Implementation experiences across various industries demonstrate substantial improvements in forecast accuracy through ML-based approaches. In retail environments, advanced forecasting models have yielded significant accuracy improvements for both regular and promotional demand periods, with particularly notable gains for fashion items and seasonal products. Manufacturing organizations have reported marked enhancements in production planning efficiency, especially for components with complex supply chains. Consumer packaged goods companies have achieved substantial reductions in forecast error rates through the integration of external market data and competitor intelligence [3]. The pharmaceutical industry has similarly benefited from improved accuracy in predicting medication demand, particularly for products with temperature-sensitive distribution requirements. These implementations have generated considerable business value through reduced stockouts, lower excess inventory, and enhanced supply chain responsiveness [4]. The most successful implementations typically feature robust data integration pipelines, careful model selection based on product characteristics, and strong organizational alignment between technical capabilities and business processes.

3. Prescriptive Analytics for Inventory Optimization

While predictive analytics forecasts future demand patterns, prescriptive analytics takes the next crucial step by recommending specific actions to optimize inventory management. This evolution from prediction to prescription represents a significant advancement in supply chain intelligence, enabling systems to autonomously determine optimal inventory policies across complex distribution networks.

3.1. Dynamic Safety Stock Calculation Methodologies

Traditional safety stock calculations often rely on static formulas that inadequately respond to fluctuating market conditions. Modern prescriptive analytics approaches have introduced dynamic safety stock methodologies that continuously adjust buffer inventory levels based on evolving demand patterns, supply variability, and service level requirements. These systems leverage machine learning algorithms to analyze historical stockout incidents, lead time variability, and forecast accuracy to determine appropriate safety margins [6]. The coverage profile approach represents a particularly effective methodology, enabling variable safety stock levels across different time horizons based on anticipated volatility. Dynamic calculation methods can incorporate seasonality factors, product lifecycle stages, and strategic important classifications to establish differentiated safety stock policies. This adaptive approach ensures that inventory buffers remain proportional to actual risk factors rather than adhering to rigid formulas, thereby minimizing unnecessary inventory while maintaining service objectives.

3.2. Multi-Echelon Inventory Optimization Strategies

The complexity of modern supply chains necessitates a holistic approach to inventory optimization that spans multiple echelons, from manufacturing facilities through distribution centers to retail locations. Multi-echelon inventory optimization (MEIO) strategies leverage prescriptive analytics to determine the optimal placement of inventory across this network, recognizing the interdependencies between stocking points [5]. These systems model the complex relationships between upstream and downstream inventories, factoring in transportation times, replenishment frequencies, and demand correlations across locations. Advanced MEIO implementations incorporate risk pooling principles, postponement strategies, and network design considerations to minimize total system inventory while maintaining service commitments. The computational requirements for these optimizations have historically presented implementation challenges, but modern machine learning approaches have enabled more efficient solutions that can rapidly recalculate optimal inventory distributions as conditions change. This network-wide perspective prevents the suboptimization that commonly occurs when each echelon manages inventory independently.

Table 2 Multi-Echelon Inventory Benefits by Sector [6, 7]

Industry	Primary Challenges	Key Benefits	Implementation Focus
Retail	Omnichannel balancing	Network inventory reduction	Point-of-sale integration
Manufacturing	Component availability	Production stabilization	Planning cycle alignment
CPG	Channel proliferation	Distribution optimization	Product categorization
Pharmaceutical	Critical availability	Compliance, reduced waste	Service level guarantees
Industrial	Service part availability	Network optimization	Installed base analytics

3.3. Scenario Simulation Techniques for Reorder Point Determination

Prescriptive analytics systems employ sophisticated simulation techniques to evaluate alternative inventory policies and determine optimal reorder points across diverse scenarios. These simulations can model thousands of potential demand patterns, supply disruptions, and market conditions to identify inventory strategies that perform robustly across a wide range of circumstances [5]. Monte Carlo methods, discrete event simulation, and digital twin approaches provide increasingly realistic representations of complex supply chain dynamics. Advanced systems can simulate the cascading effects of inventory decisions across the supply network, evaluating impacts on fill rates, cycle times, and financial metrics under various policies. These simulations facilitate the testing of innovative approaches without operational disruption, enabling organizations to quantify the tradeoffs associated with different inventory strategies before implementation. The integration of machine learning techniques has enhanced these simulations by improving parameter estimation and incorporating pattern recognition from historical disruptions into future scenarios.

3.4. Balancing Service Levels Against Inventory Costs

The fundamental challenge in inventory management involves striking an optimal balance between service level commitments and inventory carrying costs. Prescriptive analytics provides sophisticated mechanisms for quantifying this tradeoff and identifying policies that maximize overall value [6]. Advanced systems can establish differentiated service targets based on product profitability, strategic importance, and competitive positioning rather than applying uniform policies across the portfolio. These approaches incorporate detailed cost modeling, including carrying costs, obsolescence risks, handling expenses, and opportunity costs of capital. The resulting optimization frameworks enable organizations to make informed decisions about appropriate inventory investments for different product categories and customer segments. Real-time monitoring capabilities allow continuous assessment of actual service performance against targets, triggering adjustments when policies drift from optimal parameters. This systematic approach to the service-cost tradeoff represents a substantial advancement over traditional inventory management, which often relies on intuitive judgments rather than quantitative optimization.

4. Autonomous Decision-Making and System Integration

The realization of fully autonomous supply chain operations requires seamless integration between predictive analytics systems and operational platforms. This integration enables the automatic execution of analytically derived recommendations without human intervention, representing the transition from enhanced decision support to true supply chain autonomy.

4.1. ERP and SCM Platform Integration Architecture

The effective deployment of AI-driven inventory optimization necessitates sophisticated integration architectures that connect predictive and prescriptive analytics engines with enterprise resource planning (ERP) and supply chain management (SCM) platforms. These integration frameworks typically incorporate API-based connectivity, event-driven architectures, and middleware solutions that facilitate bidirectional data flows between analytical and operational systems [7]. Modern implementations leverage microservices architectures to maintain system modularity while ensuring cohesive information exchange. The integration scope extends beyond simple data transfer to include process orchestration, ensuring that analytical insights trigger appropriate operational workflows. Advanced implementations incorporate digital supply chain control towers that provide unified visibility across both analytical insights and operational execution. Security considerations, including role-based access controls and data governance frameworks, represent essential components of these integration architectures, particularly as organizations extend connectivity to external supply chain partners. This seamless connection between analytical intelligence and operational execution systems forms the foundation for autonomous supply chain operations.

4.2. Real-time Automation of Procurement and Replenishment Processes

With integration frameworks in place, organizations can implement automated procurement and replenishment processes that directly execute the recommendations generated by prescriptive analytics systems. These automated workflows typically begin with threshold-based triggers that initiate purchase orders, transfer requests, or production orders when inventory positions reach algorithmically determined reorder points [8]. Advanced implementations incorporate dynamic approval routing based on exception conditions, ensuring that human oversight remains focused on unusual scenarios while routine transactions proceed autonomously. Real-time integration with supplier systems enables automated order placement, confirmation, and tracking throughout the fulfillment cycle. The most sophisticated implementations extend automation to pricing decisions, allowing systems to adjust procurement strategies based on market conditions and supply alternatives. This transition from human-executed to system-executed operations represents a fundamental shift in operational paradigms, enabling organizations to operate with significantly greater efficiency and responsiveness to market changes.

4.3. Continuous Model Retraining and Feedback Loops

The effectiveness of autonomous supply chain systems depends critically on continuous learning mechanisms that refine both predictive and prescriptive models based on operational outcomes. These feedback loops systematically capture actual demand patterns, lead times, and stockout incidents, comparing them against forecasted values to identify prediction errors and performance gaps [7]. Advanced implementations employ automated model evaluation protocols that regularly assess forecast accuracy, bias patterns, and optimization effectiveness across different product categories and market conditions. When performance metrics fall below established thresholds, automated retraining processes update model parameters using expanded datasets that incorporate recent observations. This continuous refinement enables systems to adapt to evolving market patterns, seasonal shifts, and changing consumer preferences without manual intervention. Some organizations have implemented A/B testing frameworks that simultaneously deploy alternative forecasting and optimization approaches to subsets of their product portfolio, systematically identifying superior methodologies through comparative performance analysis.

4.4. Change Management Considerations for Implementation

The transition to autonomous supply chain operations represents a profound organizational transformation that extends beyond technical implementation to encompass cultural, procedural, and structural dimensions. Successful implementations recognize the need for comprehensive change management strategies that address stakeholder concerns regarding system transparency, decision authority, and job role evolution [8]. Organizations typically begin with phased implementation approaches that gradually expand automation scope as confidence in system performance increases. Effective governance frameworks establish clear delineation between decisions that can proceed autonomously and those requiring human review, with these boundaries evolving as system capabilities mature. Training programs that develop both technical competencies and analytical thinking skills enable supply chain professionals to transition from operational execution to exception management and strategic oversight roles.

Leadership commitment, particularly in establishing appropriate performance metrics that reward analytical adoption, proves essential for sustaining momentum through implementation challenges. The most successful organizations approach autonomy as an evolutionary journey rather than a discrete transition, progressively expanding system authority as capabilities demonstrate consistent value.

5. Industry Applications and Performance Metrics

The implementation of AI-driven predictive and prescriptive analytics for inventory management has expanded rapidly across multiple industries, with varying approaches, adoption patterns, and realized benefits. Understanding these cross-sector applications and their performance outcomes provides valuable insights for organizations considering similar transformations.

5.1. Cross-Sector Implementation Analysis

The adoption of advanced analytics for demand forecasting and inventory optimization demonstrates distinctive patterns across different industry sectors. Retail organizations have generally prioritized implementations focused on promotional forecasting, assortment optimization, and omnichannel inventory balancing to address the complexities of consumer-facing operations [9]. Manufacturing companies have concentrated on production planning integration, component-level forecasting, and multi-tier supplier coordination to enhance operational stability. Logistics providers have emphasized network optimization, transportation forecasting, and distribution center inventory balancing to maximize asset utilization. Healthcare organizations have implemented specialized solutions addressing pharmaceutical expiration management, medical supply availability, and equipment utilization forecasting. The consumer packaged goods sector has focused particularly on new product introduction forecasting, trade promotion optimization, and shelf-life maximization. While implementation approaches vary considerably across these sectors, common success factors include clear alignment with specific business challenges, staged implementation approaches, and strong integration with existing planning processes. The most mature implementations have progressed beyond functional silos to establish integrated planning capabilities that span procurement, production, distribution, and customer fulfillment operations.

5.2. Key Performance Indicators and ROI Measurements

Organizations implementing advanced analytics for inventory management employ diverse metrics to evaluate performance improvements and return on investment. Forecast accuracy metrics—including mean absolute percentage error, forecast bias, and tracking signal—provide fundamental measures of predictive performance [10]. Inventory efficiency indicators such as inventory turnover, days of supply, and carrying cost percentage help quantify the financial impact of optimization efforts. Service level metrics including fill rate, on-time delivery, and perfect order fulfillment capture the customer experience implications of inventory strategies. Cash flow metrics like cash-to-cash cycle time and working capital requirements demonstrate the broader financial implications beyond direct inventory costs. Advanced implementations increasingly incorporate resilience metrics that assess system adaptability to disruptions, including time to recovery and demand shock absorption capacity. Organizations typically establish baseline measurements before implementation and track performance improvements through a phased rollout approach. The measurement timeframe requires careful consideration, as benefits often accelerate after initial learning periods as models accumulate sufficient historical data for optimal performance. Leading organizations have developed comprehensive ROI frameworks that incorporate both tangible benefits like inventory reduction and intangible advantages such as planner productivity and decision quality improvements.

5.3. Platform Comparisons

The market for AI-enabled inventory optimization platforms has expanded significantly, with providers offering diverse capabilities and implementation approaches. Legacy supply chain software providers have extended their established solutions with enhanced analytical capabilities, typically emphasizing integration with existing planning processes and data structures [9]. Cloud-native solution providers have introduced platforms built specifically for advanced analytics, often featuring superior algorithmic sophistication but requiring more extensive integration efforts. Major cloud service providers have developed generalized forecasting services that offer scalability advantages but frequently require customization for specific industry contexts. Evaluation criteria for platform selection typically include forecast accuracy performance, model explainability, configuration flexibility, integration capabilities, and implementation complexity. Industry specialization has emerged as a significant differentiator, with some platforms developing distinctive capabilities for specific sectors like fashion retail, pharmaceutical distribution, or automotive manufacturing. Organizations increasingly approach platform selection with proof-of-concept methodologies that evaluate multiple solutions using actual company data before making enterprise commitments. The emerging trend toward composable architecture approaches allows organizations to integrate specialized capabilities from multiple providers rather than selecting a single comprehensive platform.

5.4. Challenges and Limitations in Current Implementations

Despite substantial progress, organizations implementing AI-driven inventory optimization continue to encounter significant challenges. Data quality and availability limitations frequently impede model performance, particularly for new products, intermittent demand items, and situations involving numerous external variables [10]. Integration complexity with legacy systems often extends implementation timelines and reduces realized benefits. Many organizations struggle with appropriate change management approaches, encountering resistance from planning personnel accustomed to established processes. Model explainability challenges complicate trust building and exception handling, particularly when algorithmic recommendations contradict conventional wisdom. Skill gaps in data science, statistical analysis, and AI operations present workforce challenges for many implementing organizations. The appropriate balance between automation and human judgment remains difficult to establish, with overly cautious approaches limiting benefit realization while excessive automation occasionally produces suboptimal decisions during unusual market conditions. The dynamic nature of supply chain operations necessitates continuous model maintenance and recalibration, creating sustainability challenges for organizations with limited analytical resources. Despite these challenges, leading organizations have developed mature implementation methodologies that systematically address these limitations through phased approaches, targeted skill development, and careful alignment between technical capabilities and business processes.

Table 3 Implementation Challenges and Strategies [7-10]

Challenge Category	Key Issues	Mitigation Approach	Success Factors
Data Management	Quality inconsistencies	Data governance protocols	Executive sponsorship
Organizational	Process disruption, skills	Change management program	Clear role evolution
Technical	Legacy systems, integration	API development, middleware	Architectural planning
Measurement	Benefit attribution	Metric framework, baselines	Strategic alignment
Sustainability	Model drift, maintenance	Automated retraining	Dedicated resources

6. Conclusion

The integration of machine learning and artificial intelligence into supply chain management represents a transformative advancement in demand forecasting and inventory optimization. This evolution from traditional statistical methods to sophisticated predictive and prescriptive analytics has fundamentally altered the decision-making paradigm, enabling unprecedented levels of accuracy, automation, and adaptability in supply chain operations. Implementations across diverse industries deliver substantial improvements in forecast accuracy, inventory efficiency, and service level performance while simultaneously enhancing organizational resilience in volatile market conditions. The transition toward autonomous supply chain operations continues to accelerate as integration architectures mature, enabling seamless connections between analytical intelligence and operational execution systems. While significant challenges persist—including data quality constraints, integration complexities, change management requirements, and skill gaps—effective implementation methodologies systematically address these limitations. The continued advancement of algorithmic capabilities, coupled with deeper integration across multi-enterprise supply networks, promises to further expand the possibilities in supply chain intelligence. Organizations that successfully navigate this technological evolution will likely establish significant competitive advantages through superior operational efficiency, enhanced customer responsiveness, and improved financial performance in increasingly dynamic global markets.

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