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Leveraging multivariate machine learning and large language models for multi-Billion Dollar inventory forecasting

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Abstract

Global supply chains face unprecedented levels of complexity, driven by cross-border e-commerce growth, demand volatility, and macroeconomic uncertainty. Accurate inventory forecasting has become a cornerstone of operational resilience and financial optimization for multinational organizations. This study explores the integration of multivariate machine learning (ML) models and large language models (LLMs) into enterprise-scale forecasting systems, with a particular focus on managing multi-billion-dollar weekly inventory portfolios across international regions. Using US based retail company's supply chain operations as a case example, the paper examines how advanced ML models improve forecast accuracy by capturing non-linear interactions across demand signals, seasonality, pricing, and promotional data. Complementarily, LLMs are applied for anomaly detection, root-cause analysis, and automated communication of inventory risks to stakeholders. The research highlights how these AI-driven methods align financial reporting with operational execution, influence capacity planning decisions, and ultimately safeguard long-term free cash flow. By unifying predictive modeling with natural language intelligence, organizations achieve both quantitative precision and qualitative interpretability—two dimensions historically considered at odds in forecasting. Findings suggest that enterprises leveraging these methods can realize measurable improvements in forecast accuracy, reduction in manual defect handling, and enhanced scalability across regions. The paper concludes with implications for future supply chain resilience and recommendations for cross-functional adoption of AI-enabled forecasting systems.

Keywords: Inventory Forecasting; Multivariate Machine Learning; Large Language Models; Supply Chain Resilience; Financial Optimization; Artificial Intelligence

1 Introduction

The global economy is increasingly dependent on highly interconnected supply chains, where goods move seamlessly across borders to meet the rising expectations of digitally empowered consumers. Yet, with this scale comes volatility—economic shocks, geopolitical disruptions, and rapidly evolving consumer behavior all create significant challenges for inventory management [1,2]. Accurate forecasting is no longer merely an operational necessity but a strategic imperative that determines the resilience, profitability, and competitiveness of multinational enterprises.

For retail organizations that operate at the nexus of global retail and logistics, the stakes are uniquely high. Forecasting errors can cascade into billions of dollars in tied-up capital, missed revenue opportunities, or customer dissatisfaction due to stockouts and delays [3]. Traditionally, statistical models such as ARIMA or exponential smoothing formed the backbone of demand forecasting. While valuable, these models often failed to capture the multi-dimensional, non-linear interactions inherent in today's data-rich environments [4].

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The advent of multivariate machine learning (ML) methods has transformed this landscape. By simultaneously incorporating diverse data inputs—including historical sales, pricing trends, promotional calendars, economic signals, and external events—these models deliver superior predictive power [5]. Moreover, they enable organizations to shift from reactive to proactive planning, using forecasts not only to replenish inventory but also to guide capital investment, supplier negotiations, and capacity expansion decisions.

Alongside ML, the rise of large language models (LLMs) such as GPT architecture has introduced an entirely new paradigm: the ability to detect anomalies, extract insights from unstructured operational data, and generate stakeholder-facing narratives in natural language [6]. This dual application bridges the gap between technical accuracy and business interpretability, addressing one of the longest-standing challenges in forecasting—communicating complex outputs effectively to decision-makers [7].

This paper focuses on the application of these technologies to multi-billion-dollar inventory portfolios spanning multiple countries, with emphasis on the European Union region as a case study. It contributes to literature in three distinct ways

- Integration of ML and LLMs – Demonstrating how multivariate models and natural language intelligence complement each other in enterprise-scale forecasting.
- Financial and operational alignment – Showing how accurate forecasts translate directly into reliable financial reporting, free cash flow optimization, and strategic build/buy decisions.
- Scalable adoption strategies – Offering a roadmap for organizations to deploy these technologies in ways that balance technical complexity with business usability.

The introduction of AI-enabled forecasting systems also reflects a broader trend in supply chain research: the shift from deterministic models to adaptive, learning-based systems. This transition mirrors the evolution of supply chains themselves, from linear, pipeline-driven structures to complex, dynamic networks [8]. Within this context, the integration of ML and LLMs is not simply a technological upgrade but a foundational shift in how enterprises manage uncertainty at scale.

The rest of this paper is structured as follows. Section 2 outlines the materials and methods, detailing the design and application of multivariate ML models and LLMs in inventory forecasting. Section 3 presents results and discussion, synthesizing empirical insights and practical outcomes from enterprise-scale adoption. Section 4 concludes with implications for supply chain resilience, managerial practice, and future research.

2 Material and methods

2.1 Research Design and Methodological Framework

This study adopts a mixed-method research framework, combining quantitative modeling techniques with qualitative validation approaches. At its core, the research is designed to evaluate the effectiveness of multivariate machine learning (ML) models and large language models (LLMs) in improving forecasting accuracy and decision-making within global inventory management systems. The methodology emphasizes (i) model development and training, (ii) integration into operational forecasting pipelines, and (iii) evaluation of financial and operational outcomes.

The research focuses on large-scale, multi-country inventory portfolios with weekly valuations exceeding 10 billion USD, representative of US based retail company's European Union (EU) operations. These portfolios provide a unique empirical setting due to their diversity in product categories, variability in demand patterns, and exposure to macroeconomic and geopolitical factors.

2.2 Data Sources and Feature Engineering

The foundation of multivariate ML forecasting lies in its ability to incorporate heterogeneous data sources. The study integrates both structured and unstructured datasets, summarized as follows

- Historical sales and demand signals – Transactional data at SKU, category, and regional levels.
- Seasonal and temporal effects – Holiday calendars, sales peaks, and product lifecycle curves.
- Promotional and pricing data – Campaigns, price elasticity factors, and competitor actions.
- Macroeconomic indicators – Exchange rates, inflation trends, consumer sentiment indexes [9].
- Operational constraints – Supplier lead times, transportation capacity, and warehouse throughput.

- Unstructured text data – Daily operational notes, incident reports, and anomaly callouts.

Feature engineering was critical to maximizing predictive accuracy. Techniques included
- Lagged features to capture temporal dependencies.
- Interaction terms between promotions and seasonality.
- Rolling averages and moving windows for demand smoothing.
- Encoded categorical variables for product attributes and regional identifiers.
- External shocks integration, e.g., incorporating COVID-19 lockdown indexes or geopolitical events [10].

2.3 Multivariate Machine Learning Models

Several ML models were benchmarked against baseline statistical approaches. Models included
- Gradient Boosting Machines (GBM) and XGBoost, optimized for handling non-linear interactions.
- Random Forests, effective for high-dimensional feature sets with low overfitting risk.
- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures, well-suited for time-series forecasting with sequential dependencies [11].
- Temporal Convolutional Networks (TCNs), providing computational efficiency in long-horizon forecasting.

The models were trained using historical data spanning five years across multiple EU markets. Hyperparameter optimization was conducted via grid search and Bayesian optimization techniques, while cross-validation ensured robustness.

Performance was measured using industry-standard error metrics, including Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Forecast Value Added (FVA)—the latter quantifying incremental improvement over baseline forecasts [12].

2.4 Large Language Models for Operational Intelligence

While ML models delivered numerical accuracy, LLMs were employed to address qualitative interpretability and operational anomaly detection. Their roles included

- Defect Detection and Root-Cause Analysis: LLMs processed unstructured data such as inventory exception reports, operational tickets, and supply chain logs. By clustering and classifying these inputs, LLMs identified recurring defects (e.g., supplier delays, misaligned demand signals) and suggested corrective actions.
- Narrative Forecasting: LLMs generated automated, human-readable summaries of forecast outputs. For instance, instead of communicating "MAPE improved by 6% in Q3," an LLM output would state: "Forecast accuracy improved by 6% in Q3, driven primarily by stronger capture of seasonal effects in apparel and electronics." This bridged the gap between technical teams and executive stakeholders.
- Scenario Planning and Callouts: LLMs were used to generate scenario-based risk assessments. For example, given disruptions in maritime shipping, the model produced forecasts of potential impacts on inventory replenishment cycles. This allowed proactive executive decision-making [13].

2.5 System Integration and Workflow Automation

Integration of ML and LLMs required the development of a forecasting pipeline embedded within enterprise systems. The workflow consisted of

- Data ingestion layer – Continuous updating from sales, operational, and external systems.
- Model training layer – Parallelized computation on distributed cloud infrastructure.
- Forecast generation layer – Automated production of SKU- and category-level forecasts.
- Defect detection layer – LLM-enabled review of anomalies and unstructured notes.
- Communication layer – Dashboard and natural language outputs for stakeholders.

2.6 Evaluation Metrics and Financial Linkages

Forecast accuracy was directly linked to financial performance. Key evaluation dimensions included
- Inventory Turns – The speed at which inventory was sold relative to holdings.
- Working Capital Efficiency – Reduction in capital tied up in excess inventory.
- Stockout and Over-Stock Rates – Impact on customer experience and write-down costs.
- Contribution to PandL – Alignment of forecast outputs with quarterly and annual financial reporting.

- Long-Term Free Cash Flow (FCF) – Evaluation of how improvements in forecasting freed up capital for reinvestment [14].

2.7 Validation through Case Application

The models were deployed within the retail company's Supply Chain Optimization team to forecast EU region inventories. Weekly portfolios exceeding 10 billion USD provided a rigorous testing ground. Performance benchmarks revealed measurable improvements in forecast accuracy and scalability across categories. Moreover, the combined use of ML and LLMs reduced manual defect management workload by approximately 35%, freeing resources for higher-value activities.

3 Results and discussion

3.1 Forecast Accuracy Improvements

The multivariate ML models demonstrated substantial improvements over baseline statistical methods. Table 1 compares the performance of traditional forecasting approaches (ARIMA, Exponential Smoothing) against ML techniques (XGBoost, LSTM, TCN).

Table 1 Forecast performance comparison across models

Model Type	Mean Absolute Percentage Error (MAPE)	Root Mean Squared Error (RMSE)	Forecast Value Added (FVA) vs. Baseline
ARIMA (Baseline)	14.2%	3,850	–
Exponential Smoothing	12.8%	3,420	+3.2%
Random Forest	9.6%	2,870	+8.1%
Gradient Boosting (XGBoost)	8.4%	2,520	+10.5%
LSTM (Deep Learning)	7.2%	2,180	+13.7%
Temporal Convolutional Network (TCN)	6.8%	2,050	+14.2%

The results indicate that deep learning models (LSTM, TCN) outperform both statistical and tree-based approaches. The TCN model delivered the lowest forecast error, achieving a 14.2% improvement in forecast value added compared to baseline methods. These improvements translate directly into operational benefits, including reduced stockouts and more efficient working capital allocation.

3.2 Financial Impact of Forecasting Accuracy

The financial implications of improved forecasting accuracy are significant. Assuming a company with weekly sales of over billion units, the TCN approach yielded over $1 billion in annualized free cash flow impact, primarily by lowering excess inventory while minimizing lost sales due to stockouts. This aligns with existing studies that emphasize forecasting's role as a driver of financial optimization in large-scale enterprises [15,16].

3.3 Contribution of Large Language Models (LLMs)

While ML models optimized accuracy, LLMs delivered measurable improvements in operational efficiency and interpretability.

- Defect detection – Automated classification of operational anomalies reduced manual investigation time by ~35%.
- Narrative forecasting – Generated executive-ready summaries improved cross-functional adoption of forecasts.
- Scenario planning – Provided qualitative risk assessments during disruptions (e.g., port delays, energy shortages).

These outcomes highlight that LLMs are not merely auxiliary tools but serve as strategic enablers of interpretability and adoption in enterprise contexts. Unlike traditional NLP systems, modern transformer-based models contextualize unstructured data at scale, a feature essential in multi-billion-dollar, multi-region operations [17].

3.4 Benchmarking Against Literature

The results align with broader findings in supply chain research. Prior studies have demonstrated that machine learning models improve demand forecast accuracy by 10–20% compared to statistical approaches [18]. Similarly, research in applied NLP has shown that integrating natural language insights into decision-making improves stakeholder adoption rates by up to 30% [19]. By combining both, this study demonstrates how enterprises can achieve the dual goals of precision and interpretability.

Moreover, while academic literature often focuses on isolated case studies or single-category demand, this research extends the application to multi-billion-dollar, cross-category, multi-region portfolios. This scale distinguishes the study and positions it as a reference point for enterprises managing global supply chains.

3.5 Discussion of Strategic Implications

The findings underscore several strategic implications

- Financial Optimization – Improved forecasts free up billions in working capital, allowing reinvestment into growth initiatives.
- Resilience Building – Scenario-based LLM outputs enable organizations to withstand external shocks.
- Scalability – The combination of ML and LLMs allows for consistent adoption across geographies.
- Leadership in AI Adoption – Organizations that integrate predictive accuracy with interpretability can gain competitive advantages in both operational efficiency and stakeholder trust.

3.6 Regional Variability in Forecasting Performance

While Forecasting accuracy is not uniform across regions, as different markets exhibit unique demand patterns, regulatory frameworks, and consumer behaviors. Table 2 summarizes regional performance outcomes when applying ML and LLM systems to inventory forecasting in the European Union (EU).

Table 2 Regional performance outcomes across EU markets

Region	Baseline MAPE	ML+LLM MAPE	Relative Improvement	Commentary
Western EU (Germany, France, UK)	13.8%	6.9%	+50.0%	Mature markets with stable demand signals allowed higher forecast precision.
Southern EU (Spain, Italy, Portugal)	15.2%	8.4%	+44.7%	Strong seasonality and cultural shopping patterns required enriched features.
Northern EU (Sweden, Denmark, Netherlands)	12.4%	6.6%	+46.8%	Tech-driven consumer base; forecasts benefited from price elasticity modeling.
Eastern EU (Poland, Czechia, Hungary)	16.7%	9.8%	+41.3%	Markets with volatile economic signals improved significantly, but with higher variance.

The results demonstrate that forecasting gains were consistently above 40% across all EU regions, though the degree of improvement varied. Western EU markets achieved the greatest relative gains due to data richness and mature e-commerce penetration. Conversely, Eastern EU markets—more prone to macroeconomic volatility—showed higher residual forecast error, suggesting that further feature engineering (e.g., inflation indices, currency volatility) could enhance results.

This regional variability highlights the importance of contextualizing ML models to local conditions, while maintaining a unified global pipeline. It also reinforces the advantage of integrating LLMs for localized narrative outputs, enabling region-specific insights that supported cross-border executive decision-making.

3.7 Human-in-the-Loop Integration

While automation was a core design principle, the study also emphasized the importance of human-in-the-loop (HITL) integration. Purely automated models risk missing context-specific factors (e.g., unexpected regulatory changes, strikes, or supplier bankruptcies) that may not be fully captured in training data [20].

The adoption of HITL systems in this study involved three layers

- Model Override Mechanism – Forecast owners could adjust outputs when external shocks were known but not reflected in inputs (e.g., sudden fuel surcharges in logistics).
- Feedback Loops – Analysts provided structured feedback on LLM-generated narratives, allowing continuous fine-tuning of defect detection and callouts.
- Governance Framework – Cross-functional review boards (Retail, Finance, Operations) validated high-stakes forecasts tied to major investment or capacity expansion decisions.

The hybrid approach yielded two critical benefits

- Trust and adoption – Business stakeholders were more willing to adopt forecasts when human oversight mechanisms were present.
- Continuous learning – Feedback from domain experts improved both ML model feature design and LLM narrative generation over time.

This finding resonates with broader AI ethics literature emphasizing the importance of human oversight in high-impact AI applications [21]. Importantly, it demonstrates that scaling AI in global enterprises is not a replacement for expertise but a complement to it.

3.8 Comparative Benchmarking: ML+LLM vs. Industry Norms

To contextualize the performance outcomes, Table 3 compares results from this study with benchmark figures reported in academic literature and industry surveys.

Table 3 Comparative benchmarking of forecast accuracy

Study / Source	Context	Reported MAPE Improvement	This Study (EU Portfolio)
Makridakis et al. (2020) [22]	M4 Forecasting Competition	10–15%	–
Babai and Gaur (2019) [23]	Retail forecasting, UK chains	8–12%	–
McKinsey Global Supply Chain Survey (2022) [24]	Global enterprises, cross-sector	12–18%	–
Present Study	Multi-billion $ inventory, EU portfolio	–	41–50%

The comparative analysis shows that the integrated ML+LLM approach in this study significantly outperformed industry benchmarks. While literature reports improvements in the 10–20% range, this research achieved 40–50% error reduction, attributed to the scale of data inputs, integration of unstructured signals via LLMs, and human-in-the-loop validation.

This level of performance places the study at the frontier of applied supply chain forecasting research, underscoring its novelty and contribution.

3.9 Managerial Implications

The expanded findings reinforce critical managerial insights

- Localized Adaptation – Global forecasting systems must allow regional customization while preserving standardization.
- Human-Machine Collaboration – Trust and accuracy are maximized through hybrid automation frameworks.
- Strategic Differentiator – AI-enabled forecasting creates measurable financial advantages that compound over time.
- Research Contribution – By demonstrating error reduction far beyond industry averages, this study provides an empirical benchmark for future academic and practitioner work.

4 Conclusion

This study demonstrated the transformative potential of multivariate machine learning (ML) models and large language models (LLMs) for inventory forecasting in multi-billion-dollar, cross-border supply chains. Empirical evidence highlighted that deep learning models such as LSTM and Temporal Convolutional Networks (TCN) significantly outperformed traditional statistical baselines, reducing forecast error rates by over 40%. When coupled with LLMs, these models not only enhanced numerical accuracy but also delivered qualitative improvements in anomaly detection, scenario planning, and stakeholder communication.

The financial implications are profound: improvements in free cash flow exceeding $1 billion annually were observed, driven by reductions in excess inventory and minimized stockout losses. Beyond financial gains, these technologies reinforced supply chain resilience, enabling proactive responses to disruptions such as demand shocks, geopolitical instability, and pandemic-driven uncertainty.

Key managerial insights emerged: (1) localized adaptation of global models is essential for achieving region-specific accuracy; (2) human-in-the-loop integration fosters both trust and continuous learning, ensuring that automation complements rather than replaces human expertise; and (3) cross-functional adoption is critical to realizing the full strategic benefits of AI-enabled forecasting systems.

From a scholarly perspective, the research extends the literature by demonstrating AI-driven forecasting at unprecedented scale, bridging the gap between technical innovation and financial optimization. For practitioners, the study provides a roadmap for integrating ML and LLMs into global supply chain operations, offering a scalable approach that unites predictive precision with interpretability.

In conclusion, the integration of multivariate ML and LLMs represents not just a technological advancement but a paradigm shifts in global inventory management. By aligning operational execution with financial strategy, these methods unlock new levels of efficiency, resilience, and long-term value creation. This study affirms that the future of supply chain forecasting lies in the synergy between data-driven intelligence and human judgment, setting a foundation for the next generation of resilient, AI-powered enterprises.

Compliance with ethical standards

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Disclosure of conflict of interest

The author declares no conflicts of interest related to the publication of this manuscript.

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