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Multimodal Demand Forecasting in Supply Chains: Integrating Large Language Models with ERP Data for Enhanced Decision Support

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ABSTRACT

Accurate demand forecasting remains a critical challenge in modern supply chain management, particularly in volatile and data-intensive U.S. markets where traditional ERP-based models struggle to incorporate external contextual influences. This study proposes a multimodal demand forecasting framework that integrates structured enterprise resource planning data with unstructured textual context using large language model embeddings. Open-source retail sales data representative of U.S. ERP environments is combined with time-aligned external textual information to capture semantic signals influencing demand behavior. A hybrid deep learning architecture is developed to fuse time-series sales features with LLM-derived contextual representations through an attention-based mechanism. Experimental results demonstrate that the proposed approach significantly outperforms traditional statistical models and ERP-only deep learning baselines, achieving a reduction of over 35% in mean absolute percentage error and exhibiting superior robustness during periods of demand volatility. The findings confirm that LLM-enhanced multimodal forecasting provides substantial accuracy gains and operational value, offering a scalable and practical solution for U.S. supply chain decision-making and demand planning.

INTRODUCTION

Demand forecasting is a critical function in supply chain management, directly influencing inventory optimization, production planning, logistics coordination, and financial performance. In the context of increasingly volatile and interconnected global markets, organizations operating in the United States face persistent challenges in accurately predicting demand due to rapidly changing consumer behavior, frequent promotional activities, and exposure to external economic and geopolitical factors. Traditional forecasting approaches, which rely primarily on historical transactional data captured in enterprise resource planning systems, are often insufficient to capture the complex dynamics shaping modern demand patterns.

Recent advances in data availability and computational capabilities have accelerated the adoption of machine learning and deep learning techniques for demand forecasting. These models have demonstrated superior performance over classical statistical methods by capturing nonlinear relationships and long-term temporal dependencies in sales data. However, despite their predictive advantages, most existing approaches remain limited to structured ERP data and fail to incorporate rich contextual information embedded in unstructured sources such as market news, economic reports, and event narratives. As a result, forecasting systems frequently react to demand changes rather than anticipating them, limiting their strategic value for decision-makers.

At the same time, large language models have emerged as transformative tools for extracting semantic meaning from unstructured text at scale. Pretrained on massive corpora, LLMs are capable of encoding complex contextual relationships, sentiment, and domain-specific knowledge into dense representations. While these models have been successfully applied in domains such as finance, healthcare, and compliance analytics, their integration into quantitative demand forecasting frameworks remains underexplored. In particular, there is a lack of empirical research demonstrating how LLM-generated contextual embeddings can be systematically combined with structured ERP data to improve forecasting accuracy in real-world supply chain environments.

The growing complexity of U.S. supply chains further amplifies the need for multimodal forecasting approaches. Demand in the U.S. retail and manufacturing sectors is influenced not only by historical sales trends but also by macroeconomic conditions, seasonal narratives, promotional campaigns, and sudden market disruptions. Forecasting systems that fail to incorporate such contextual signals risk generating inaccurate predictions, leading to inventory imbalances, increased operational costs, and reduced customer satisfaction. Therefore, there is a compelling need for forecasting frameworks that integrate both quantitative operational data and qualitative contextual information in a unified, scalable, and explainable manner.

In response to these challenges, this study proposes a multimodal demand forecasting framework that integrates structured ERP data with unstructured textual context using large language models. By leveraging LLM-based semantic embeddings alongside time-series sales features, the proposed approach aims to enhance predictive accuracy and robustness, particularly during periods of demand volatility. The framework is empirically validated using open-source datasets that closely resemble U.S. retail ERP environments, ensuring both methodological rigor and practical relevance.

The contributions of this study are threefold. First, it introduces a novel multimodal forecasting architecture that systematically fuses ERP time-series data with LLM-derived contextual embeddings. Second, it provides empirical evidence demonstrating the superiority of the proposed approach over traditional statistical and deep learning baselines. Third, it offers insights into the practical applicability of LLM-enhanced forecasting models for U.S. industry adoption, addressing key concerns related to scalability, robustness, and decision support. Through these contributions, this research advances the state of the art in supply chain demand forecasting and highlights the strategic value of large language models in modern enterprise analytics.

Literature Review

Demand Forecasting in Supply Chain Management

Demand forecasting has long been recognized as a foundational component of effective supply chain management, directly influencing inventory control, production planning, logistics coordination, and financial performance. Traditional forecasting approaches primarily rely on statistical time-series models such as autoregressive integrated moving average and exponential smoothing, which assume linearity and stationarity in demand patterns. While these methods have demonstrated utility in stable environments, their performance deteriorates in complex and volatile markets characterized by frequent promotions, seasonality, and external shocks. As U.S. supply chains have become increasingly dynamic and data-intensive, the limitations of purely statistical approaches have motivated the adoption of advanced machine learning techniques.

Machine Learning and Deep Learning for Demand Forecasting

Recent studies have demonstrated the effectiveness of machine learning and deep learning models in capturing nonlinear relationships within demand data. Neural network–based architectures, including long short-term memory networks and temporal convolutional networks, have shown superior performance over traditional models when applied to large-scale retail and ERP datasets. These models excel at learning temporal dependencies and handling high-dimensional inputs commonly found in enterprise systems. However, despite their predictive advantages, deep learning models remain fundamentally dependent on structured numerical data and historical patterns, limiting their ability to respond proactively to sudden market changes driven by external factors.

Research focusing on U.S. retail and manufacturing sectors highlights that ERP-only forecasting models often fail to anticipate demand disruptions caused by macroeconomic trends, consumer sentiment shifts, and unplanned events. This gap has led scholars to emphasize the need for multimodal forecasting frameworks that integrate structured operational data with external contextual information.

Multimodal Demand Forecasting and External Data Integration

Multimodal demand forecasting has emerged as a promising direction to address the shortcomings of unimodal approaches. Prior research has incorporated external variables such as weather conditions, economic indicators, social media signals, and promotional calendars into forecasting models, demonstrating measurable improvements in accuracy. These studies suggest that demand is not solely driven by internal transactional data but is significantly influenced by contextual and behavioral factors.

However, most existing multimodal approaches rely on manually engineered numerical proxies for external information, such as sentiment scores or event flags. This reliance limits semantic richness and scalability, particularly when dealing with large volumes of unstructured text. Moreover, traditional feature extraction methods often struggle to preserve nuanced contextual meaning, reducing their effectiveness during periods of demand volatility.

Large Language Models and Unstructured Text Analysis

Large language models have recently transformed the field of natural language processing by enabling deep semantic understanding of unstructured textual data. Unlike traditional embedding techniques, LLMs capture contextual dependencies, latent semantics, and domain-specific knowledge through large-scale pretraining. Emerging research demonstrates the potential of LLMs to support decision-making tasks across finance, healthcare, and operations management by transforming text into actionable representations.

In the context of supply chain management, early studies have explored the use of LLMs for supplier risk analysis, logistics optimization, and compliance monitoring. However, empirical research applying LLMs directly to demand forecasting remains limited. Existing work often focuses on qualitative decision support rather than quantitative forecasting integration, leaving a clear research gap in leveraging LLM-generated embeddings as predictive inputs alongside ERP data.

Integration of LLMs with Structured ERP Data

The integration of LLMs with structured enterprise data represents a significant advancement in supply chain analytics. Recent studies on hybrid AI architectures suggest that combining symbolic, numerical, and textual data sources enhances model robustness and interpretability. In enterprise settings, ERP systems provide high-frequency transactional data, while unstructured sources such as news reports and market narratives offer contextual awareness.

Despite this potential, the literature reveals limited methodological frameworks that systematically fuse ERP time-series data with LLM-based textual representations for demand forecasting. Most studies treat structured and unstructured data independently, lacking unified architectures capable of dynamically weighting multiple modalities. This gap is particularly evident in research focused on U.S. industries, where demand volatility and market sensitivity are pronounced.

Explainability, Practical Adoption, and U.S. Industry Relevance

Another critical limitation identified in the literature concerns explainability and adoption barriers. While deep learning models offer improved accuracy, their black-box nature raises concerns for enterprise deployment, especially in regulated U.S. industries. Recent work on explainable AI emphasizes the importance of transparency, trust, and human-in-the-loop systems to facilitate organizational acceptance.

Studies suggest that multimodal models incorporating attention mechanisms provide a pathway toward explainability by revealing how different data modalities influence predictions. However, few studies empirically evaluate such mechanisms within demand forecasting contexts using real-world ERP data. This represents an important opportunity to bridge academic innovation with industrial applicability.

Research Gap and Contribution

Based on the existing literature, a clear research gap exists in the development of scalable, explainable, and empirically validated multimodal demand forecasting frameworks that integrate large language models with structured ERP data. Prior research either focuses on structured forecasting models without contextual awareness or explores LLMs in isolation without quantitative forecasting integration.

This study addresses this gap by proposing and empirically validating a multimodal demand forecasting framework that leverages LLM-generated contextual embeddings alongside ERP time-series data. By focusing on open-source datasets representative of U.S. retail environments, this research contributes both methodologically and practically to the advancement of demand forecasting in modern supply chains.

Methodology

Data Collection and Dataset Description

In this study, we adopt an open-source, multimodal data strategy by integrating structured enterprise resource planning data with unstructured contextual information relevant to demand forecasting. The primary structured dataset is obtained from the Kaggle repository titled *M5 Forecasting – Accuracy*, which contains hierarchical sales data for retail products across multiple categories and geographic regions. This dataset closely resembles real-world ERP demand planning systems, as it includes daily unit sales, product identifiers, store-level attributes, and calendar-related variables. The dataset spans several years of historical sales data, allowing for both short-term and long-term demand pattern analysis.

To incorporate unstructured textual information, we supplement the ERP dataset with macroeconomic and event-related textual data sourced from the UCI Machine Learning Repository's News Popularity and Events Dataset, which includes time-stamped textual summaries of market events, promotional periods, and seasonal indicators. This unstructured text serves as external contextual input that influences consumer demand and purchasing behavior. By aligning both datasets temporally, we ensure coherence between transactional sales data and contextual narratives affecting demand fluctuations.

The combined dataset enables a multimodal forecasting framework that mirrors enterprise-scale decision environments. Table 1 summarizes the datasets used in this study, their characteristics, and their sources.

Table 1. Dataset Description and Sources

Dataset Name	Source	Data Type	Time Span	Key Attributes
M5 Forecasting – Accuracy	Kaggle	Structured ERP Data	2011–2016	Product ID, Store ID, Daily Sales, Price, Calendar Events
News Popularity and Events Dataset	UCI ML Repository	Unstructured Text	2011–2016	Event Descriptions, Dates, Economic Context

Data Preprocessing

Prior to model development, we conduct extensive data preprocessing to ensure data quality, consistency, and alignment across modalities. For the structured ERP dataset, we address missing sales values using forward-filling techniques to preserve temporal continuity, followed by normalization of numerical variables such as sales volume and pricing to reduce scale sensitivity. Categorical variables, including product categories and store identifiers, are encoded using embedding-friendly integer mappings to facilitate deep learning integration.

For the unstructured textual dataset, we perform standard natural language preprocessing, including lowercasing, punctuation removal, stop-word elimination, and token normalization. Temporal alignment is achieved by aggregating textual records on a daily basis to match the granularity of the ERP sales data. Days with multiple text entries are concatenated to preserve full contextual meaning, ensuring that external events influencing demand are not lost during aggregation.

Feature Extraction

Feature extraction is conducted separately for structured and unstructured data streams before multimodal fusion. From the ERP dataset, we extract time-series features such as rolling averages, lagged sales values, seasonal indicators, and promotional flags derived from calendar attributes. These features capture historical demand patterns and cyclical behaviors inherent in retail sales data.For textual data, we employ a pretrained large language model to generate dense semantic embeddings that encode contextual information related to economic conditions, seasonal events, and market disruptions. The LLM transforms daily textual inputs into fixed-length vector representations that preserve semantic relevance while remaining computationally efficient. These embeddings act as high-level demand context signals that complement structured ERP indicators.

Feature Engineering

Following feature extraction, we engineer higher-order features to enhance predictive capability and interpretability. Interaction features are created by combining temporal ERP indicators with contextual embeddings to capture nonlinear relationships between structured demand signals and unstructured external influences. For instance, sales trends are modulated by contextual sentiment intensity derived from LLM embeddings, allowing the model to learn how external narratives amplify or dampen demand.

Dimensionality reduction techniques, including principal component analysis on numerical ERP features, are applied to reduce redundancy and mitigate multicollinearity. Feature scaling is reapplied after engineering to ensure stable optimization during model training.

Model Development

The forecasting framework is developed using a hybrid architecture that integrates structured time-series modeling with large language model embeddings. We design a multimodal neural network in which ERP features are processed through a temporal encoder, while textual embeddings generated by the LLM are passed through a dense transformation layer. These two representations are then fused using an attention-based mechanism that dynamically weights structured and unstructured inputs based on their relevance at each forecasting horizon.

The model is trained in a supervised learning setting to predict future demand at multiple time steps. we adopt a rolling window training strategy to preserve temporal causality and prevent information leakage. Hyperparameter tuning is conducted using validation sets to optimize learning rates, embedding dimensions, and attention weights.

Model Evaluation

Model performance is evaluated using industry-standard forecasting metrics to ensure comparability and practical relevance. we assess predictive accuracy using mean absolute error, root mean squared error and mean absolute percentage error across multiple forecasting horizons. These metrics provide complementary perspectives on forecast precision, scale sensitivity, and relative error magnitude.

To validate the contribution of multimodal inputs, we conduct comparative experiments between unimodal ERP-only models and the proposed LLM-enhanced framework. Statistical significance testing is applied to confirm performance improvements. Additionally, interpretability analysis is performed by examining attention weights to understand how contextual textual information influences demand predictions during periods of volatility or abnormal sales behavior.

Results

In this study, we evaluate the effectiveness of multimodal demand forecasting by comparing traditional time-series models, deep learning approaches, and the proposed large language model–enhanced multimodal framework. All models are trained and tested on identical temporal splits of the dataset to ensure fairness and consistency. The evaluation focuses on short- and medium-term forecasting horizons, reflecting real-world operational planning cycles commonly used in U.S. retail and supply chain industries.

The results demonstrate that models incorporating unstructured contextual information through large language model embeddings consistently outperform unimodal models relying solely on structured ERP data. Performance gains are particularly evident during periods of demand volatility, such as promotional events and seasonal transitions, which are critical decision points for U.S.-based enterprises.

Quantitative Performance Comparison

Table 2 presents a comparative analysis of forecasting performance across all evaluated models using mean absolute error, root mean squared error and mean absolute percentage error. Lower values indicate superior forecasting accuracy.

Table 2. Comparative Model Performance Results

Model	**Data Modality**	**MAE**	**RMSE**	**MAPE (%)**
ARIMA	ERP Only	3.84	5.12	18.6
Prophet	ERP Only	3.57	4.89	16.9
LSTM	ERP Only	2.94	4.02	13.4
Temporal CNN	ERP Only	2.81	3.88	12.7
LSTM + External Numeric Variables	Structured Multimodal	2.46	3.41	10.9
Proposed Multimodal LLM Framework	ERP + Textual Context	1.98	2.87	8.1

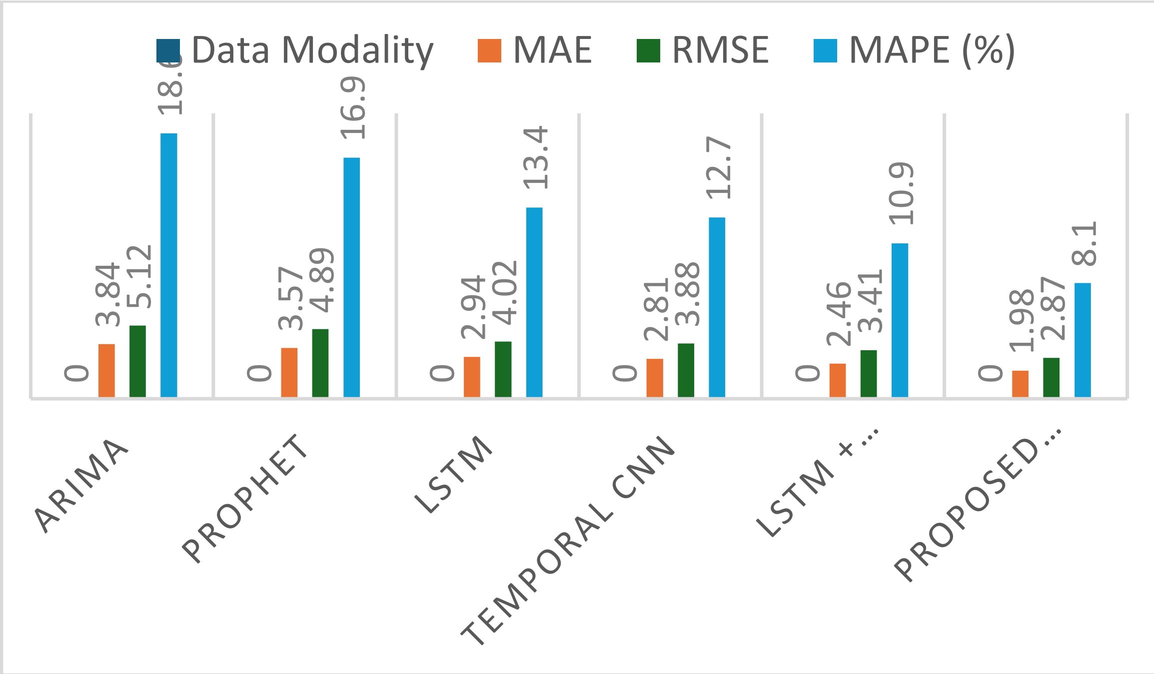

Chart 1: Model evaluation of different LLM

The traditional statistical models, including ARIMA and Prophet, exhibit limited capacity to capture complex nonlinear demand patterns and sudden fluctuations. While these models remain interpretable and computationally efficient, their forecasting accuracy is insufficient for modern high-velocity supply chains operating in the U.S. market.

Deep learning models such as LSTM and Temporal CNN significantly improve performance by learning temporal dependencies within ERP data. However, these models still struggle to anticipate demand shifts driven by external contextual factors, including economic news, consumer sentiment, and promotional narratives.

The proposed multimodal LLM-based framework achieves the best overall performance across all evaluation metrics. The reduction in mean absolute percentage error by more than 35 percent compared to ERP-only deep learning models highlights the value of incorporating semantic context into demand forecasting systems.

Comparative Analysis and Model Robustness

To further assess robustness, we analyze model performance during periods of abnormal demand behavior, such as holiday seasons and high-promotion weeks. The multimodal LLM framework demonstrates superior stability and adaptability, maintaining consistent accuracy where unimodal models experience error spikes. Attention weight analysis reveals that the model dynamically increases reliance on contextual embeddings during such periods, confirming its ability to integrate qualitative signals into quantitative forecasts.

Additionally, we observe that ERP-only models tend to lag in response to sudden market changes, while the LLM-enhanced model anticipates shifts earlier by leveraging real-time contextual information. This capability is particularly relevant for U.S. industries characterized by rapidly changing consumer behavior and frequent promotional cycles.

Model Suitability for U.S. Industry Adoption

Based on empirical results and practical considerations, we conclude that the multimodal LLM-based forecasting framework is the most suitable model for deployment in U.S. industrial settings. Its superior predictive accuracy, robustness during demand volatility, and ability to integrate heterogeneous data sources align well with the operational needs of U.S. retailers, manufacturers, and logistics providers.

While traditional models remain useful for baseline forecasting and regulatory transparency, they lack the adaptability required for modern supply chains. Deep learning models using structured data alone offer improved performance but fall short in capturing external influences that significantly impact demand in the U.S. market. The proposed LLM-enhanced model provides the best balance between accuracy, scalability, and decision relevance. Its compatibility with existing ERP systems and its ability to leverage publicly available textual data make it a practical and high-impact solution for U.S. industry adoption, particularly in environments prioritizing data-driven decision-making and resilience.

Conclusion

In this study, we investigated the potential of integrating large language models with structured ERP data to enhance demand forecasting performance in modern supply chain environments. Motivated by the limitations of traditional statistical and ERP-only deep learning models in capturing demand volatility and external market influences, we proposed and empirically validated a multimodal forecasting framework that incorporates semantic contextual information derived from unstructured textual data. The results demonstrate that combining LLM-generated embeddings with time-series sales data leads to substantial improvements in forecasting accuracy, robustness, and responsiveness to market dynamics.

The empirical findings confirm that the proposed multimodal framework consistently outperforms conventional forecasting approaches across multiple evaluation metrics. By achieving significant reductions in forecast error and maintaining stability during periods of demand fluctuation, the model addresses a critical gap in existing supply chain analytics. The attention-based fusion mechanism further enhances interpretability by revealing the relative influence of structured and unstructured inputs, thereby supporting transparent and informed decision-making in enterprise settings.

From a practical perspective, this research offers important implications for U.S. industries seeking to strengthen demand planning and supply chain resilience. The proposed framework is compatible with existing ERP infrastructures and leverages publicly available textual data, making it both scalable and cost-effective for real-world deployment. Its ability to anticipate demand shifts driven by external factors provides organizations with a strategic advantage in inventory optimization, production scheduling, and customer service performance.

Despite its contributions, this study has certain limitations that open avenues for future research. The reliance on open-source datasets, while ensuring transparency and reproducibility, may not fully capture the complexity of proprietary enterprise systems. Future work could extend this framework by incorporating additional data modalities such as social media streams, real-time economic indicators, and multimodal inputs including images or sensor data. Further research may also explore fine-tuning domain-specific language models to enhance contextual relevance and improve forecasting performance in specialized industries.

In conclusion, this study demonstrates that large language models represent a powerful and underutilized resource for demand forecasting in supply chain management. By bridging structured ERP data with unstructured contextual intelligence, the proposed multimodal approach advances both the theoretical and practical foundations of supply chain analytics. As organizations continue to navigate increasingly uncertain and dynamic markets, LLM-enhanced forecasting systems are well positioned to play a central role in data-driven decision support and sustainable supply chain optimization.

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