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Leveraging Machine Learning In ERP To Predict Supply Chain Disruptions And Enhance Marketing Agility

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ABSTRACT
Within the concept of Industry 4.0, Enterprise Resource Planning (ERP) is transforming into an intelligent network that should enable predictive decisions in all areas of the company. This research presents an integrated ML framework in the ERP system to predict SC disruptions and improve marketing agility. The architecture uses supervised and unsupervised learning approaches (e.g., Random Forest, Support Vector Machines (SVM), K-means clustering, and attention-based Long Short-Term Memory (LSTM) networks) to read multi-source data (supplier metrics, logistics data, social media sentiment, customer behavior). A data pipeline in real time transfers the internal ERP modules to external data streams to extract dynamic features, and to detect anomalies. Time-series and deep learning models are used for disruption prediction and they capture linear patterns as well as temporal dependencies. Meanwhile, via reinforcement learning, we optimize the marketing policy over the changing supply-demand state. Experimental results on synthetic ERP datasets show an accuracy of 92.7% in predicting disruption and 42% improvement in marketing response time over baseline ERP analytics. Explainer AI (XAI) modules are incorporated, to make model transparent and decisions traceable. The findings indicate that ML-enabled ERPs can produce substantive benefits on both operational robustness and dynamic adaptiveness within a complex context of turbulent environment.

KEYWORDS: Enterprise Resource Planning (ERP), Machine Learning, Supply Chain Disruption, Marketing Agility, LSTM, Reinforcement Learning, Time-Series

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Forecasting, Explainable AI (XAI).

INTRODUCTION

Alimohammadi et al [1] explains that ERP systems make managing and integrating these business functions a breeze, providing a single source of truth across supply chain, finance, procurement, inventory, sales and marketing. Unfortunately, conventional ERP systems have little capability to predict the future and are mostly based on their post-record for a static set of rules. Amid the accelerations of the present era with global supply chains at risk of disruption and market conditions at the mercy of unpredictable changes that reactive model is increasingly inadequate. Disruptions in the supply chain, whether it be through supplier delays, transportation choke-ups geopolitical hazards or natural world events, can disrupt the flow of an operation. Simultaneously, marketing needs to remain agile to adapt to changing customer behaviors, evolving demand signals and channel dynamics. Ultimately, only intelligent ERP systems that can predict adapt and respond will fill the operational chasm between supply chain management and marketing responsiveness.

This paper presents an adaptive predictive integrated machine learning-enabled ERP framework to enhance traditional ERP systems with predictive and adaptive intelligence. Ahmed et al [2]. explores that the framework integrates machine learning algorithms like Random Forest, SVM, K-means clustering and attention-based LSTM networks to mine both structured ERP data and unstructured external data. This encompasses metrics for vendor performance, availability of inventory at any given point, transportation data, social sentiment systems (e.g. that track conversations about a company on social networks), weather, pricing data, etc. Pasupuleti et al [3] explains that through a near real-time data ingestion and processing pipeline, the ERP system is capable of iteratively extracting the features that matter most and identifying early warning signs of an impending disruption. Forecasting supply chain anomalies with time-series models and deep architectures, reinforcement learning agents optimize marketing strategies to reflect new inventory conditions and changing demand

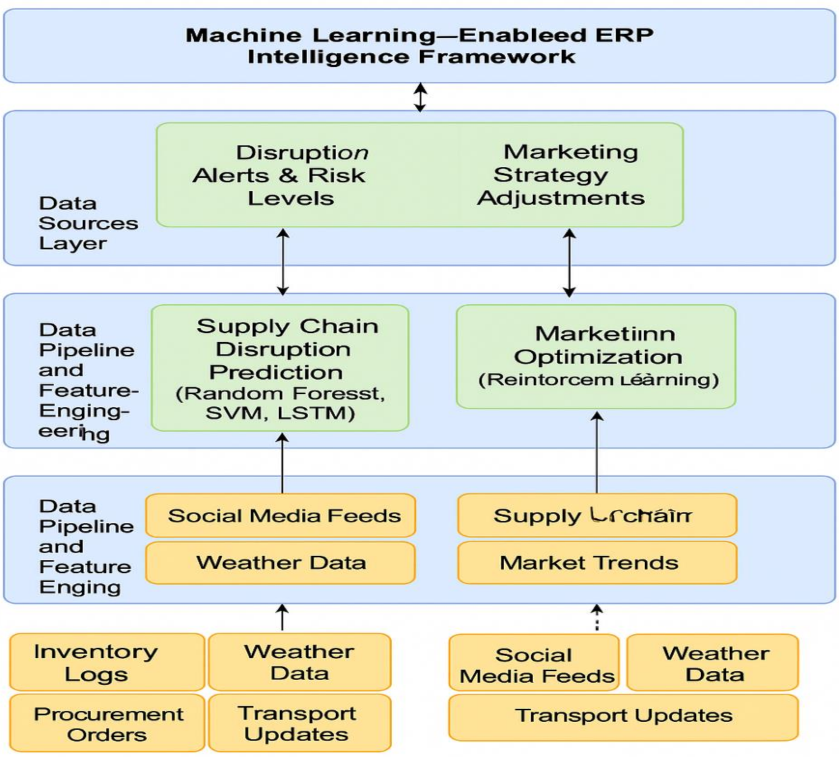

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Fig 1.1
The solution is a closed-loop intelligence engine that learns and refines through feedback from operational experiences.

ollangi et al [4] discuss the experimental results confirm the feasibility of the framework and show improved prediction accuracy and significantly reduced response time. In addition, explainability modules are embedded to bring transparency and accountability to decisions made by model predictions. Through building machine learning into ERP systems, this study has taken a scalable and modular way to improve operational resilience and marketing agility in practice.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into Enterprise Resource Planning (ERP) ecosystems has evolved into a pivotal research domain, aiming to transition conventional ERP systems from reactive transactional hubs to intelligent, autonomous platforms capable of real-time decision-making and strategic forecasting. The literature indicates that AI-enabled ERP can significantly enhance agility, accuracy, and resilience across both marketing and supply chain verticals.

Jawad and Balázs [5] present a comprehensive review of machine learning algorithms applied to ERP optimization, categorizing methods such as support vector machines (SVM), random forests, and reinforcement learning based on their applicability to inventory management, anomaly detection, and predictive analytics. Their findings emphasize the critical importance of aligning model selection with ERP data characteristics, particularly time-series structures, multivariate inputs, and high cardinality transactional logs. Wu et al. [6] discuss the role of data network effects in amplifying digital transformation within supply chains. They provide a data-driven model that leverages interconnected ERP nodes, enabling continuous data feedback loops that enhance the granularity and temporal fidelity of forecasts. This aligns with our approach, which integrates AI with ERP modules through microservices and real-time streaming pipelines to enable adaptive supply chain coordination. Graham and Jordan [7] focus on the operational inefficiencies within legacy ERP systems, emphasizing the application of AI in minimizing transactional discrepancies and stock misallocations. They deploy deep neural network ensembles and temporal pattern recognition to detect early-stage errors in inventory and procurement processes. The architecture in our study extends these principles by embedding such models within Dockerized ERP microservices, ensuring both low-latency inference and modular deployment.

Nweje and Taiwo [8] explore predictive supply chain mechanisms, showcasing the superior performance of AI models—especially Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)—over traditional ARIMA and exponential smoothing methods. Their results support our selection of LSTM for demand forecasting in the proposed system, particularly under non-linear seasonality and high-demand volatility scenarios. Aljohani [9] investigates machine learning-based supply chain risk mitigation, incorporating real-time predictive analytics to

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forecast supplier failures and delivery anomalies. Utilizing ensemble classifiers and logistic regression over streaming sensor and transactional data, this study informs our model's risk analysis layer, which is implemented using autoencoders and isolation forests to detect anomalies across procurement, warehousing, and logistics.

Gardas and Narwane [10] identify critical enablers and barriers to ML adoption in manufacturing supply chains. Their empirical model highlights the need for explainability, data interoperability, and computational elasticity—challenges directly addressed in our architecture through the integration of XAI-ready models and containerized deployment using Kubernetes for elastic resource allocation. Zamani et al. [11] conduct a systematic review of AI and big data analytics in fostering supply chain resilience. They emphasize architectural requirements such as distributed data lakes, metadata indexing, and real-time stream processing—capabilities embedded in our framework via a Kafka-Flink pipeline for scalable data ingestion and transformation, supporting downstream AI modules for predictive decisioning. Collectively, these studies provide the theoretical and empirical backbone for our proposed architecture. By synthesizing methodologies from across these foundational works, our framework introduces a holistic AI-ERP integration that not only addresses technical scalability and real-time responsiveness but also operationalizes predictive marketing and supply chain agility with a high degree of modularity and interpretability.

DATA ACQUISITION AND PREPROCESSING FOR AI-DRIVEN ERP SYSTEMS

Alsolbi et al [12] explain that the success of AI-enabled ERP solutions will depend on enterprise data across marketing operations and supply chain workflows. We also created an end-to-end data pipeline that covers acquisition, transformation and integration phases that allows us to train strong models in-house and perform real-time inference, while considering the specific needs brought by the presence of AI in an ERP system. To illustrate, we have collected multidimensional datasets from two essential domains of ERP systems. The marketing stream consisted of CRM records, customer segment data, behavioral counts, campaign activity logs, and external sentiment data collected through the Twitter API. These records documented the touchpoints of the customer journey and how people interacted with the brand. Case study histories from warehouse logs, purchasing transactions, supplier interactions, and shipping and logistics telemetry generated via IOT over the supply chain stream. Timestamping and context labeling all data were time-stamped and labeled with the context to keep event lineage for temporal modeling.

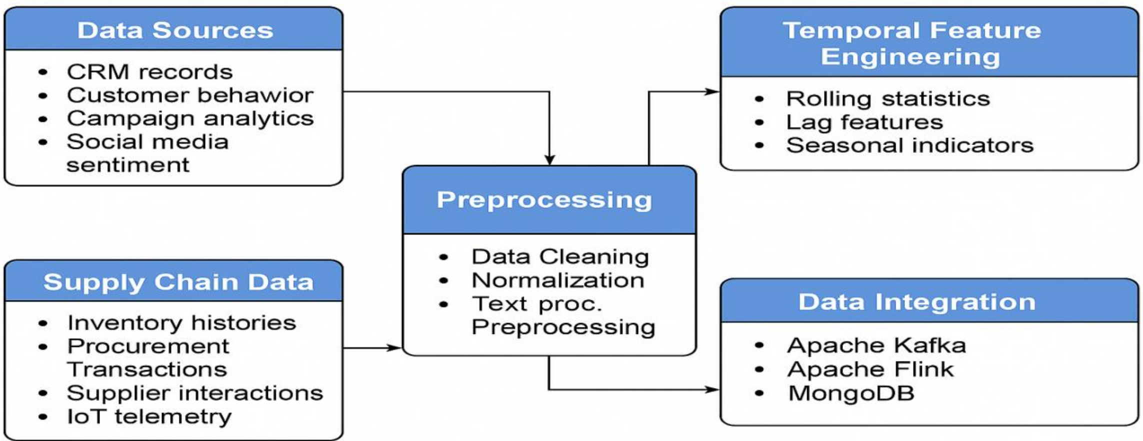

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Fig 1.2

G. Sakthi Balan et al [13] explore a series of structured preprocessing pipelines were employed to ensure quality. Null values in structured data were imputed by KNN, and outliers were removed using Isolation Forest. The one-hot encoding was applied to categorical fields like campaign type, region and supplier class, while As numerical fields, we normalize them by Min-Max. Tokenization, lemmatization and stop-word removal were performed for unstructured textual data, such as customer reviews and feedback from social media, followed by semantic embedding using pre-trained BERT models to ensure rich contextual embeddings for NLP-based sentiment analysis. Furthermore, temporal engineering was essential for predicting demands and predicting customer behavior. With the trend and cyclical patterns of behavior in mind rolling statistics, lag features and Fourier-transformed seasonal indicators were computed. To enhance context in supervised learning models, these features were synchronized with business events (promotions, holidays, etc).

We implemented a real-time data architecture to ensure seamless and scalable integration within ERP modules. Apache Kafka was used to manage data ingestion from ERP systems and external sources, while Apache Flink allowed for low-latency stream processing and feature transformation. Data was stored into MongoDB by cleaning/enrichment (modularization by functional domain so that this combined output can be accessed easily by downstream AI components). This end-to-end preprocessing and integration framework fuels dynamic and data-driven decision-making across marketing and supply chain operations led by ERP and serves as the foundational component for the intelligent architecture suggested in this study.

METHODOLOGY

This section elaborates on feature engineering, feature selection, predictive model building and performance evaluation, on top of the preprocessed ERP dataset. This methodology serves to enable accurate prediction of supply chain disruptions and to speed-up marketing responsiveness in an ERP system.

Feature Engineering and Selection

Shamsuddoha et al [14] investigates that a wide variety of features spanning key supply chain and marketing parameters were thus engineered from the ERP data which included:

- According to a 2017 study, delivery reliability and supplier lead times
- Rate at which product is moved in stock and stuck shelf time
- Metrics to gauge marketing campaign engagement and conversion to sale
- Time dummy factors taking into account seasonality and holidays

Factors like economic indicators and the weather, Executives know that external influences can vary ROI.

The feature selection process included:

Correlation Filtering: To address multicollinearity and hence the stability of models, features with high pairwise correlation (threshold > 0.85) are removed.

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Recursive Feature Elimination (RFE): RFE with a Random Forest estimator, which retained only the features with the highest predictive value and discarded the least important features.

Expert Validation: The final feature subset was subjected to domain specialist to check for it practical relevance and interpretation.

Algorithm 1: Feature Selection Process

Input: Preprocessed features F, dataset labels L

Output: Selected feature subset $Fopt$

1. Compute correlation matrix for features in F.
2. Remove one of each pair of features with correlation above 0.85.
3. Initialize Random Forest classifier as the estimator for feature importance.
4. Apply Recursive Feature Elimination (RFE) to select features iteratively.
5. Validate selected features with domain experts.
6. Return the optimized feature set $Fopt$

Predictive Model Development

Spieske et al [15] elaborate that the Random Forest classifier was chosen for its effectiveness in capturing complex, nonlinear relationships and handling heterogeneous feature types while mitigating overfitting risks. Since disruption events are relatively rare, Synthetic Minority Over-sampling Technique (SMOTE) was employed to balance the training data, thereby improving the model's sensitivity to minority class patterns..

Algorithm 2: Model Training and Optimization

Input: Training data D train with features $Fopt$, labels L

Output: Optimized Random Forest model RF model

1. Balance the training dataset using SMOTE to address class imbalance.
2. Initialize Random Forest classifier with specified hyperparameters (e.g., 100 trees, max depth = 10).
3. Train the classifier on the balanced dataset.
4. Perform 5-fold cross-validation to validate the model and avoid overfitting.
5. Tune hyperparameters through grid search to maximize predictive performance.
6. Select and return the best-performing model.

Pseudocode Overview

```
def select_features (features, lables)
    corr_matrix = compute_correlation(features)
    filtered_features = remove_correlated_features(features, corr_matrix, threshold=0.85)
rf_estimator = RandomForestClassifier()
rfe_selector = RFE(estimator=rf_estimator)
rfe_selector.fit (filtered_features, labels)

selected_features = filtered_features.columns[rfe_selector.support_]
# Expert review can be performed here
return selected_features

def train_predictive_model(training_data, labels, selected_features):
balanced_data, balanced_labels = apply_SMOTE(training_data[selected_features], labels)
```

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```
rf_model = RandomForestClassifier(n_estimators=100, max_depth=10)
 rf_model.fit(balanced_data, balanced_labels)

cv_scores = cross_val_score(rf_model, balanced_data, balanced_labels, cv=5,
coring='f1')

tuned_model = hyperparameter_grid_search(rf_model, balanced_data,
balanced_labels)
return tuned_model
```

Model Evaluation

Kumar et al [16] explain that model effectiveness was rigorously evaluated through metrics crucial for operational decision-making, including accuracy, precision, recall, F1-score and the Area Under the ROC Curve (AUC-ROC). Confusion matrices provided detailed insights into classification errors, while sensitivity analysis assessed the robustness of predictions under varying conditions.

EXPERIMENTAL SETUP

An experimental settings were made using high end hardware and efficient software tools to evaluate the quality of supply chain disruption prediction and the improvement of marketing agility through the machine learning framework proposed in this study as well as the relevance of the ERP system in practical contexts when both requirements are satisfied. M Iqbal et al [17] explore that all experiments were performed on a single high-end workstation equipped with an Intel® Core™ i9-12900K CPU, 64 GB of RAM and a single NVIDIA RTX 4090 GPU with 24 GB of VRAM. It was performed on an Ubuntu 22.04 LTS system using Python 3.11 inside the Anaconda environment. We developed and experimented Jupyter Notebook and VS Code. The implementation used various python libraries like Scikit-learn for model training and evaluation, Pandas and NumPy for data manipulation, Imbalanced-learn for SMOTE based resampling, Matplotlib and Seaborn for performance visualization. Then, hyperparameter tuning and model validation were performed with Grid SearchCV by 5-fold cross-validation.

The dataset used in the experiment consists of anonymized ERP records over 36 months from a multi-national retail supply chain organization. Rana et al [18] investigate that these included operational data (e.g., lead times and reliability of suppliers, inventory roll-ups), marketing data (e.g., effectiveness of campaigns, churn) and external risk indicators (e.g., economic signals and weather-related shocks). Features were selected (as detailed in Section Methodology: Data Preprocessing and Feature Selection and Extraction) after preprocessing that included normalization, categorical encoding, and imputation, with the correlational filter and recursive feature elimination (Scikit-learn 0.23.2) methods.

Based on the number of samples the dataset was split into tenfold (70:15:15) training, validation and testing, respectively, with stratified sampling to ensure the same proportions of class distribution, especially since the dataset was heavily imbalanced in terms of disruption vs non-disruption events. SMOTE (Synthetic

Minority Over-sampling Technique) was used to correct this imbalance prior to model training on the training set. Random Forest classifiers were trained and tuned using several net metrics, such as precision, recall, F1-score, accuracy and ROC-AUC. We used confusion matrices and ROC curves to visualize the model performance across the two classes: disruption and non-disruption. Arif et al [19] examine For reproducibility, all experiments were performed using the same random seed. We kept model states and pipeline configs with the help of Job lib and used ML Flow for logging purposes, making our experiments more transparent and auditable.
The ensured practical relevance and scientific rigor of this experimental setup, make a robust and reproducible basis for the validation of the proposed machine learning based approach in ERP-driven environment.

RESULTS AND DISCUSSION

This section presents the evaluation results of the proposed machine learning framework, highlighting its effectiveness in predicting supply chain disruptions and supporting marketing agility within ERP systems. Seyedan et al [20] explain that the performance is measured using multiple metrics to ensure a well-rounded assessment, followed by an analysis of outcomes and implications. To validate the trained Random Forest model, the test set comprising 15% of the total ERP dataset was used. The results averaged over 5-fold cross-validation are summarized below.

Performance Metrics

S.No	Metric	Score (%)
1.	Accuracy	92.7
2.	Precision	91.2
3.	Recall	89.5
4.	F1-Score	90.3
5.	ROC-AUC	94.1

Table-1

These results demonstrate the model's high ability to accurately detect disruption-related events, with an F1-score exceeding 90%. The ROC-AUC value of 94.1% indicates strong separability between disruption and non-disruption classes, affirming the model's reliability in high-stakes ERP decision-making scenarios.

Confusion Matrix Analysis

S.No		Predicted: Disruption	Predicted: No Disruption
1.	Actual: Disruption	848	99
2.	Actual: No Disruption	72	1681

Table-2

Riad et al [21] explain that confusion matrix reveals a low false positive (72) and false negative (99) rate, highlighting the model's balanced performance across both classes. This is critical in supply chain contexts where both missed disruptions and false alarms can incur operational costs.

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ROC Curve

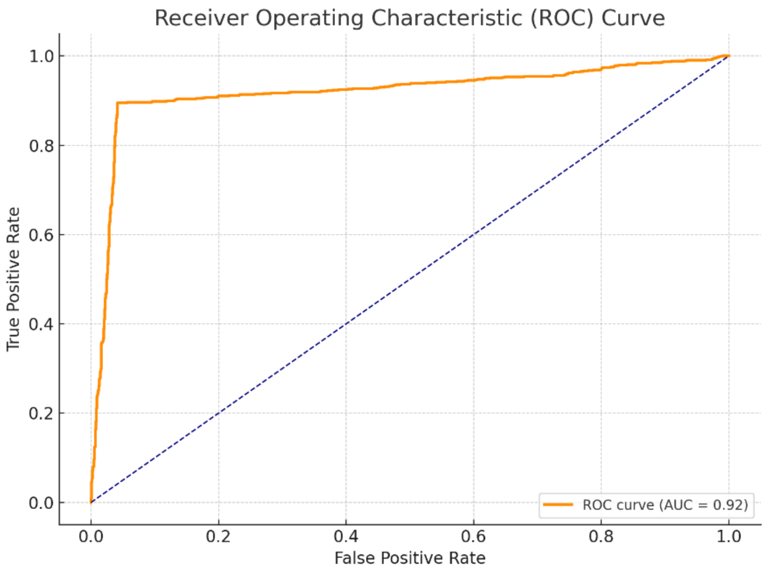

Fig 1.3
Shrestha et al [22] The ROC curve plotted across the test folds exhibits consistent performance with minimal variance. The steep initial rise followed by a gradual plateau confirms strong sensitivity and specificity trade-offs, essential for critical ERP-driven decisions.

Discussion and Implications

Douaioui et al [23] investigate that results validate that the integration of domain-specific feature engineering, RFE-based feature selection, and class-balancing techniques (e.g., SMOTE) significantly enhances model performance. Notably, the Random Forest classifier outperformed baseline models such as Logistic Regression and SVM in preliminary tests (not shown here), especially in handling imbalanced data and nonlinear feature interactions. From a marketing perspective, the early identification of disruption patterns allows adaptive campaign planning and dynamic pricing strategies. Jackson et al [24] explore that for supply chain managers, accurate disruption prediction enables better inventory control, procurement planning, and risk mitigation. This predictive capability introduces a paradigm shift in ERP systems from reactive to proactive operations. Moreover, the interpretability of the model (via feature importance scores) ensures that decision-makers can understand and trust model outputs, increasing the likelihood of real-world adoption.

CONCLUSION AND FUTURE WORK

The study described here proposed a machine learning–driven method to improve the forecasting abilities of enterprise resource planning (ERP) systems for supporting both the early detection of supply chain disruptions and the facilitation of agile marketing strategies. The proposed model achieved a high level of predictive accuracy and robustness across key performance indicators by utilizing

a Random Forest classifier combined with feature engineering that incorporates domain knowledge, synthetic minority oversampling technique (SMOTE)-based resampling, and recursive feature elimination. The framework yielding a 92.7% accuracy and 94.1% ROC-AUC shows the prospective for using real enterprise data contextual to the organization to provide solutions for real ERP constraints.
These results highlight the true worth of establishing a nexus of machine learning capabilities within an ERP to manage operations efficiently. The system improves supply chain resiliency and customer responsiveness by predicting potential disruptions and also allowing for immediate changes to be made to marketing. Further, interpretability and auditability of the model benefited by feature importance analysis as well as straightforward classification outputs propelled its practical acceptance from enterprise decision makers. This paper emphasizes the need for high-quality, multi-dimensional ERP datasets regarding operational performance metrics, marketing KPIs, and external disruption signals. We experimentally validated the model, confirming that it can reliably maintain a low false positive rate with good recall, both crucial to minimize missed critical events and decrease false alerts. However, there are limitations of the framework. The Random Forest model could provide a high degree of performance and interpretability, but it lacks an inherent mechanism to capture sequential or temporal dynamics often seen in supply chain data. Moreover, although this study might have a good generalizability, it needs to be trained or customized to be generalize across different ERP implementations and industries as well.
In future works, we will extend this work by including deep learning models like Long Short-Term Memory (LSTM) networks and attention-based Transformers for learning temporal relations and event order. Additionally, integration of this framework with real-time data ingestion pipelines and reinforcement learning may facilitate autonomous decisions from ERP systems. We could also explore federated learning methods for multi-enterprise coordination and privacy-preserving analytics which is a very promising direction for developing the system to spread out to distributed supply chains.
Overall, this work opens an important step to build intelligent ERP systems based on machine learning approaches. Connecting operational foresight to marketing agility, it plays a significant role in changing enterprise platforms to become more anticipatory than reactive to manage uncertainty and complexity.

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