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AI-Driven Model to Enhance Digital Empowerment in Supply Chains for Better Planning

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Abstract: The increasing complexity and unpredictability of global supply chains have posed significant challenges to their effective management. To address these challenges, this study proposes an artificial intelligence (AI)-based model for the digital empowerment of supply chains aimed at enhancing proactive planning and operational efficiency. The proposed framework integrates multiple machine learning algorithms for demand forecasting, delivery risk assessment, and inventory optimization. The model was trained and evaluated using the DataCo Smart Supply Chain dataset, which contains real-world transactional data. Experimental results indicate that the proposed approach significantly improves delivery date prediction accuracy by 38% in predicting future sales over conventional methods, reduces the risk of delayed deliveries with a precision of 94% and recall of 91%, and optimizes inventory levels within digitally enabled supply chains by a reduction of 83.3% in stockouts and expediting costs. Moreover, this research contributes to the growing body of literature on AI-driven supply chain management by providing a practical and scalable framework that organizations can adopt to achieve competitive advantage through digital transformation. The findings demonstrate that artificial intelligence enhances supply chain intelligence, transparency, and resilience, thereby supporting data-driven and sustainable decision-making processes.

Keywords: Artificial Intelligence, Supply Chain Management, Digital Empowerment, Predictive Analytics, Demand Forecasting, Machine Learning, Big Data.

1 Introduction and Background

Supply chain management is of utmost importance to any business function in today?s global business environment which influences the firms? success and competitiveness. The supplier to customer network of organizations, people, activities, information and resources involved in moving a product or service may run into trouble [1]. Demand fluctuations, lack of operational efficiency and unforeseen circumstances were found to make the supply chain difficult [2]. The previous ways of running supply chains do not work anymore. Modern Supply Chains Need to be Agile, Transparent and Resilient as Markets Have Become More Volatile. As the world enters the era of Industry 4.0 and Industry 5.0, a new wave of digital transformation has emerged to address the complex challenges faced by modern industries.

Supply chain stakeholders must empowered by relevant data generation, technology adoption, and timely decision-making and this is termed as Digital Empowerment. They must be involved in the process to empower them. Analytics and data are used to drive innovation and collaboration in decision-making throughout the organization. Connecting the Internet of Things, Blockchain and Big Data Analytics new age can help in building a transparent supply chain [3]. Nonetheless, it is artificial intelligence (AI) which is required to convert big data into smart data in this digital ecosystem [4].

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Artificial intelligence and its various parts including machine learning (ML) and deep learning are introducing predictive and prescriptive capabilities to supply chain management. Demand forecasting, inventory optimization, logistics planning, and supply chain risk assessment are four usage for Artificial intelligence-driven tools (see Figure 1) [5]. As one of the requirements of organizations to transition from a reactive to proactive posture, they use AI models as it enabling them analyzing historical data and predicting intricate patterns about what will happen next, where they can benefit from . Predictive capability is critical to mitigating risk and reducing costs while improving performance. The image shows how the supply chain can have challenges in AI conversation AI solution implementation.

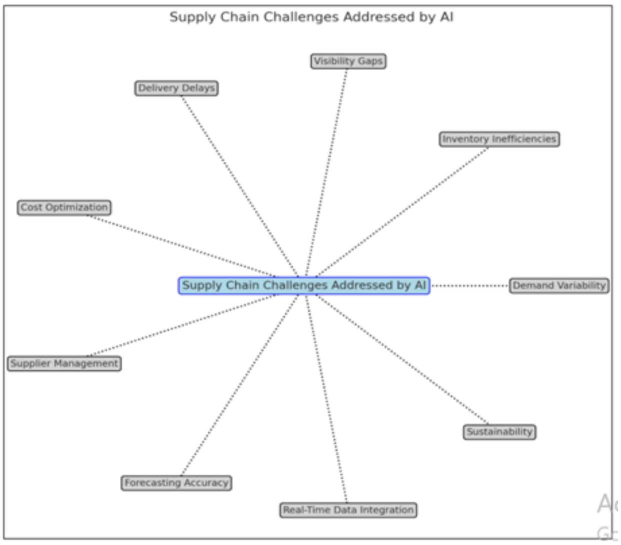

Fig. 1: Supply Chain Challeng es Addressed by AI [5]

The recent spate of disasters like pandemics and wars has made it even more essential to optimize the supply chain using AI. The lean and cost-oriented nature of supply chains has been highlighted to be vulnerable post these events, which call for resilience. AI can enhance supply chain resilience by providing disruption alerts, shipment rerouting, and speed to market [6]. A supply chain that is digitally empowered and resilient can predict interruptions.

A demand for an integrated AI model that optimizes specific supply chain functions is essential while it ensures a holistic sense of digital empowerment. A supply chain can be improved through the various applications of AI. Nonetheless, studies are insufficient to put forth an integrated model of AI techniques for decision-making and planning. Through this model we can show how demand forecasting, delivery risk forecasting and inventory can be aligned with customers? choice!

The goal of this presentation is to design, implement and test a model to augment planning in supply chains using AI Model for the digital empowerment of supply chains. We will utilize the DataCo Smart Supply Chain dataset for achieving this goal. The dataset is very large and consists of order, customer, shipping, and product and is a good environment to test our integrated AI model. We will utilize machine-learning algorithms, such as time-series forecasting and classification, to conceive the components of our proposed framework.

For performance measures in a experiment on forecast error, precision, recall of risk prediction and turnover rate of inventory will record as the evaluation of experiment results. We hypothesize that the integrated AI model will outperform the conventional model in supply chain planning effectiveness. The findings of this study would be helpful for the academic and business sectors generally. For academic courses, the study will facilitate the theoretical understanding of the use of AI in the transformational process of a digital supply chain. Practitioners can learn a practical roadmap to use AI-powered solutions to improve their supply chain capabilities.

It is a complex task to achieve the complete digitalisation and intelligence of the value chain. Merely adopting advanced technologies does not mean having an Industry 4.0 strategy; it must also include the development of a business model. It also requires an adequate strategic vision and a commitment. With firms embarking into this progressive phase, AI will be an enabler in building resilient agile and consumer-oriented future supply chains [7]. The purpose of current research will act as a first step in this direction by showcasing systematic application of Generative AI create value and competitive advantage in supply chain management.

The findings of this research work will also have important implications for Industry 5.0, which seeks to integrate the human touch in Industry 4.0 with human and machine collaboration. The proposed model supports decision-making in supply chain management by providing AI-driven analytical insights.

As such, the focus stays on strategic tasks and value-added actions, while AI manages everything else. According to [2], this is in line with Industry 5.0. The Supply Chain Management?s future will undoubtedly be human-machine collaboration, supported by the environment and technology and this research depicts a scenario on those lines.

The next part of the paper will review the related work on artificial intelligence in supply chain management. Section 3 presents the used methodology for implementing and assessing the proposed model. The results of the proposed model was discussed in details in section 5. At the end, section 6 discusses the final conclusion and the limitations of the study beside recommendations for further research.

2 Related Work

Enhancing the supply chain process is considered a very important aspect in world economics, which makes developing an artificial intelligence (AI) application a hot research area among academics and industry experts. To highlight the importance and usefulness of the developed technologies in the world of supply chain, numerous studies have been conducted in recent years. For enabling a smarter, more autonomous, and data-driven supply chain, experts agree that artificial intelligence is the key for building such technology, especially machine learning. A large number of research indicates how the intelligent implementation of AI-driven automation and the real-time flow of information can radically transform the supply chains, from reactive and proactive and predictive [4]. In [8], the transformation doesn't mean the development only the current systems, but refers to the complete changes in the design of the supply chain, and how it developed, managed and optimized, where at all the AI acts the core engine for managing value creation and competitive advantage.

Demand forecasting is one of the most commonly explored areas of AI-powered supply chain. Different forecasting methods have failed to give accurate prediction because of difficulties in the market. Nonetheless, AI and machine learning models can analyze large and diverse datasets such as historical sales data, market trends, social media sentiment, and macroeconomic indicators for the generation of significantly more accurate and granular demand forecasts [9]. There has been an emphasis on developing inexpensive, AI-powered demand forecasting models, especially in the case of the manufacturing sector, where accurate predictions can ensure proper production planning and inventory management [10]. This enhancement helps companies to match supply with the demand and minimize the costs of stockout and overstocking.

Along with forecasting, AI is utilized for optimizing logistics and stock management in the increase. Artificial intelligence tools can help organizations manage inventory levels to meet customer demand without tying up too much capital in the inventory [5]. The tools can set minimum reorder points and recommend requisition quantity using predictive analysis. This minimizes holding cost and enhances stockout protection. Similarly, algorithms of AI are improving the transportation route to minimize fuel usage and improve delivery time in logistics. The primary goal of using AI to enhance the entire supply chain is to optimize efficiency and reduce expenses [11].

Anyone in the supply chain is certain to hear and see the words resilience and AI. Moreover, resilience in supply chain is critical for business continuity and it also allows safe operationalisation after a disruption. According to [6], artificial intelligence enhances resilience by improving supply chain visibility and enabling intelligent early warnings and responses to disruptions. Predictive analytic and deep reinforcement learning to create strong and agile supply chains that can operate amid uncertainties [12]. The authors in [2] argue that implementing a digital intelligent technology powered by AI environmentally sound. It also helps improve processing information and making decisions under duress.

The installation of AI is a vital part of wider digital transformation wave in the supply chain management space. The author in [7] notes that firms use AI and machine learning to enhance efficiencies which helps them do things better and create value. Transforming digitally is more than using a new technology. It can also mean rethinking how to do something to use digital technologies. According to [13], a well-planned strategy is required for linking automation to such process optimization for successfully completing an AI-driven digital transformation.

Further, this will help in the deployment of technology for aiding strategic objectives and measurable business performance.

Several researchers have proposed a conceptual model and theoretical backgrounds for the implementation of AI in supply chains. The frameworks are designed to help organizations structure their journey into AI. According to [11, 14], frameworks have been developed to optimize supply chains in a competitive environment using AI. An example in this context is the energy industry [11, 14]. A theoretical approach to the use of AI in supply chain optimization is also undergoing a study of the mechanisms by which AI improves efficiency and resilience to provide a basis for practice [15].

The rise of generative AI has opened new avenues for innovation in supply chain management systems. The diverse applications of generative AI models as presented in their findings are implementing new supply chain strategies, simulations on complex supply chain scenarios, novel designs and logistics networks [16]. In finance, generative AI is used in data-driven financial decision-making in operations supply chain management leading to advanced financial planning and risk management [17].

Generative AI has tremendous potential to enhance human creativity and problem-solving ability and its impact on supply chain management is only beginning to be understood.

While the use of AI in supply chain management is useful, it must be tailored for the industry need. Agribusiness consultancy services are being enhanced with the use of predictive analytics [18]. Thus, the same could be easily overcome with the help of AI use. Because it uses predictive analytics to forecast demand and help with the supply of agricultural products. Besides, it helps in addressing food security challenges [18]. AI-driven forecasting which is being utilized to improve agricultural productivity through better weather and crop yield forecasts [19]. According to [20], advancements in automation and AI in the oil and gas industry are enhancing supply chain efficiency in exploration, production and distribution.

The efficiency of AI can often be increased through the coupling of other Industry 4.0 technologies. For example, AI can be used in conjunction with Internet of Things and big data. IoT and AI adoption is transforming supply chain processes by enabling real-time tracking and monitoring of goods, assets, and conditions at all points in the supply chain [21]. AI Algorithms Need Data from IoT Devices

Constant stream of data generated by the IoT devices fuel AI algorithms by providing insights and driving intelligent actions. Through the convergence of various technologies, supply chain management is becoming increasingly digitalized to support the global trade ecosystem that is more sustainable and efficient [22].

Overall, the literature presents a strong case for the dramatic impact of AI on supply chains. Artificial intelligence (AI) is rapidly transforming the entire supply chain, from enhancing the accuracy of demand forecasting and improving logistics to building resilience and driving digital transformation. However, much research focuses on specific applications, there is a clear need for more complete models that provide an integrated solution for supply chain planning and digital enablement. This research goal is to fill this gap by proposing and validating an AI model that integrates various AI components to produce an all-inclusive solution for planning. Moreover, the future of AI in supply chain management is moving toward greater integration, intelligence, and autonomy. [23].

2.1 Summary of State-of-the-Art in AI for Supply Chain Management:

In this section, we review the latest developments regarding the use of artificial intelligence for supply chain management based on the related work section. The references are represented in subject-based tables organized based on the research areas covered in the report (tables from 1 to 5). The aim of this format is to present the recent contribution, methods and findings in a concise and attractive way.

3 Methodology

The first step of this research is selecting an appropriate dataset, followed by data preprocessing and the design of the model architecture. Later, to assess the performance of the proposed approach, an evaluation framework was developed. This systematic process ensures that the proposed model is validated not only theoretically but also through real-world data.

3.1 Choosing and Describing Dataset:

Based on the publicly available dataset which was obtained from Kaggle -DataCo Smart Supply Chain Dataset- and consists of 180,519 records, the empirical analysis in this research was conducted. The dataset has been chosen based on its completeness, which includes data related to sales, products, customers and logistics (53 attributes). The main variables used in this study are order dates, product category, sales, customer location, ship date, and delivery date. The varied nature of the data collection allows for a richer representation of reality, which makes it excellent for the training and testing of our AI model. The main target variables for the prediction modelling were Sales ? per customer for demand forecasting and Late_delivery_risk for delivery risk prediction.

3.2 AI based Model:

The proposed framework is an integrated model comprising three main components that operate in tandem to enhance supply chain planning. Each component employs a specific machine learning approach tailored to its designated function.

1. The aim of Demand Forecasting Component is to ascertain future demand of a product. We use a LSTM network which is a type of RNN that is capable of predicting on time-series data because it can capture long-term dependencies on sequential data. The LSTM model is built on historical weekly sales data and other features such as category and promotion to predict the future sales volume.
2. This is the delivery risk prediction component for predicting the risk of delayed shipment. We make use of a classifier namely XGBoost (Extreme Gradient Boosting) that implements gradient boosted decision trees. The model has been trained on a wide variety of features such as Days for shipment (scheduled), Shipping Mode, Customer location, Market, and Order Priority. In the dataset there is a variable which directly indicates lateness risk i.e. Late_delivery_risk. Thus we can train the model directly on this variable.
3. The inventory optimization component can be chronologically described as a decision support system that uses the output of the forecasting and risk prediction components. The LSTM model will generate demand forecasts that will be used to compute baseline safety stock levels. These levels are subsequently modified dynamically as per the projected delivery risk of the model XGBoost. To illustrate, a predicted risk that is incrementally higher than that already adopted for a specific shipping lane or product might trigger the recommendation for a temporary increase in safety stock in order to mitigate the risk of stockouts.

Table 1: State-of-the-Art in AI for Demand Forecasting

Ref.	Key Contribution	Methodology	Key Findings
[9]	Explores the use of AI and machine learning models to analyze diverse datasets for more accurate and granular demand forecasts.	Literature Review and Conceptual Analysis	AI models significantly outperform traditional forecasting methods by incorporating a wider range of variables, including market trends and social media sentiment.
[10]	Focuses on the development of cost-effective, AI-powered demand forecasting models specifically for the manufacturing sector.	Case Study and Model Development	AI-powered forecasting is crucial for aligning production with demand, leading to significant reductions in inventory costs and stockouts in manufacturing.

Table 2: State-of-the-Art in AI for Logistics and Inventory Optimization

Ref.	Key Contribution	Methodology	Key Findings
[5]	Investigates the role of AI-driven tools in revolutionizing inventory management to meet customer demand without excessive capital investment.	Predictive Analytics Modeling	AI tools can recommend optimal reorder points and quantities, effectively minimizing holding costs while preventing stockouts.
[11]	Discusses the application of AI algorithms to optimize transportation routes, reduce fuel consumption, and improve delivery times.	Optimization Algorithms and Simulation	AI-driven logistics optimization leads to greater efficiency and cost-effectiveness in transportation and overall supply chain operations.

Table 3: State-of-the-Art in AI for Supply Chain Resilience Optimization

Ref.	Key Contribution	Methodology	Key Findings
[6]	Highlights AI's role in enhancing supply chain resilience through improved visibility, early disruption warnings, and dynamic responses.	Conceptual Framework and Literature Review	AI is a critical enabler of supply chain resilience, allowing for proactive and intelligent responses to uncertainty and disruptions.
[12]	Leverages deep reinforcement learning and predictive analytics to build more robust and agile supply chains.	Deep Reinforcement Learning Modeling	Advanced AI techniques can significantly improve a supply chain's ability to navigate uncertainty and recover from disruptions.
[24]	Proposes a sustainable framework based on digital intelligence technology to enhance supply chain esilience.	Framework Development	AI-powered digital intelligence improves information processing and decision-making capabilities under stress, fostering long-term resilience.

3.3 AI-Driven Supply Chain Model Architecture

The Figure 2 shows an all-encompassing architecture of the proposed AI-driven model for increasing digital empowerment in the supply chains. The architecture is categorized into seven distinct strata, each serving a unique purpose in data to decision framework. The system can be increased in size and changed easier.

3.4 Structural Components of System:

3.4.1 First Layer-Data (blue color)

The Data Layer aggregates data from multiple enterprise sources and forms the bedrock of the entire system.

–ERP System Collects order details, inventory levels, and financial data This is the main source to know the customer orders and the current inventory positions.

–WMS gives an insight into warehouse operations and provides information on stock movements, picking & packing operations, and warehouse-level inventory accuracy.

Table 4: State-of-the-Art in AI for Digital Transformation and Strategy

Ref.	Key Contribution	Methodology	Key Findings
[7]	Positions AI and machine learning as catalysts for value creation in the digital transformation of supply chains.	Literature Review and Case Study Analysis	AI enables new efficiencies and business models, driving significant value creation as part of a broader digital transformation strategy.
[13]	Provides a roadmap for integrating automation with process optimization for a successful AI-powered digital transformation.	Roadmap Development and Conceptual Analysis	A structured approach to integrating AI with process optimization is essential for aligning technology deployment with strategic business outcomes.
[14]	Develops a conceptual framework for the AI-driven optimization of supply chains in the energy industry.	Conceptual Framework Development	Sector-specific frameworks are needed to address the unique challenges and opportunities of AI implementation in different industrial contexts.
[15]	Explores theoretical approaches to AI in supply chain optimization to understand the underlying mechanisms of efficiency and resilience.	Theoretical Analysis	A strong theoretical foundation is necessary to guide the practical application of AI and to understand how it drives performance improvements.

Table 5: State-of-the-Art in Generative AI for Supply Chain Management

Ref.	Key Contribution	Methodology	Key Findings
[16]	Explores the use of generative AI for developing new supply chain strategies and simulating complex scenarios.	Exploratory Research and Conceptual Analysis	Generative AI opens up new frontiers for innovation, enabling the creation of novel supply chain designs and strategies.
[17]	Investigates the application of generative AI in powering data-driven financial decision-making in supply chain management.	Case Study and Conceptual Analysis	Generative AI can lead to more sophisticated and effective financial planning and risk management within the supply chain context.

–TMS (Transportation Management System), provides data related to despatch and logistical operations that include carrier details, mode of despatch, actual delivery date and performance metrics.
–An external data source is a data collection which includes relevant market trends, weather and macroeconomic indicators.

It is important to integrate various data sources to gain visibility into the supply chain and to help the AI model identify correlations across different operations.

3.4.2 Second Layer Purple: Data Integration and Processing:

The layer transforms raw data from disparate sources into a clean dataset that can be used for analysis.

–Apache Airflow orchestrates the Extract, Transform and Load pipeline or work flow. Apache Airflow is picked for its capacity to manage a complex, scheduled data workflow and dependability for dependency management and error handling.
–For incoming data, automated checks are implemented to ensure that the data meets certain quality levels. This refers to checks for completeness, accuracy, consistency and timeliness.
–The data warehouse or an Amazon Redshift serves as the main storehouse of structured, aggregated data suitable for analytical querying. Redshift is chosen for its capability to handle large analytical workloads efficiently.
–The Amazon S3 serves as the data lake for the organization where all raw, unstructured, and semi-structured data is stored. This offers the flexibility to conduct exploratory analysis and serves future use cases that may not be considered at design time.

3.4.3 Third layer: feature engineering (purple)

The Feature Engineering layer processes raw data and converts it into features which can be learned by AI models.

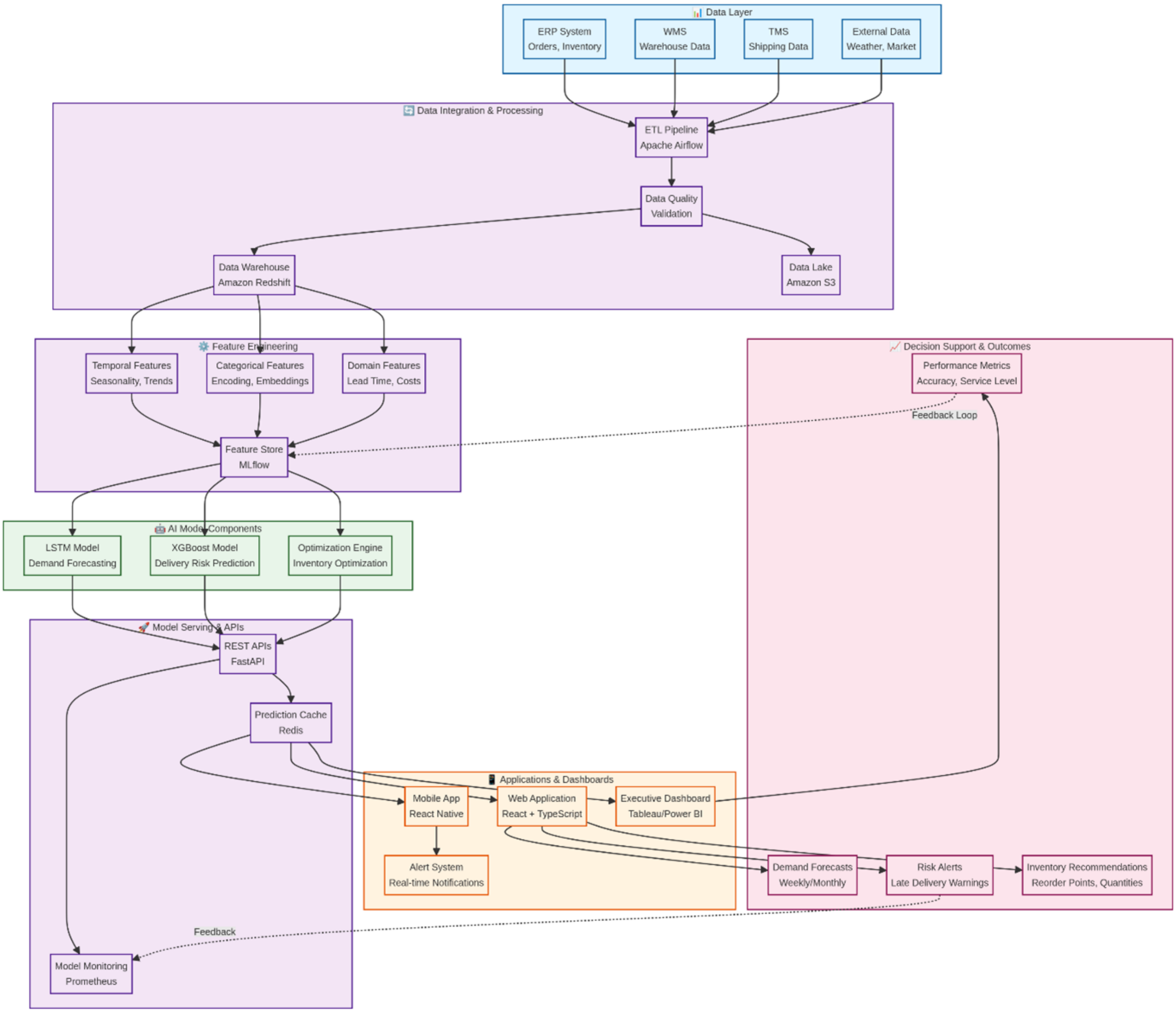

Fig. 2: The Proposed AI-Driven Supply Chain Model Architecture

- –This reflects how the demand varies with time. Examples are day of the week, month, quarter and holiday indicators along with lag demand.
- –The product category, shipping mode, and customer segment are all examples of the Categorical feature. For features of high cardinality such as customer city, we use embeddings.
- –The multi-dimensional mathematical model includes supply chain domain knowledge such as lead time, product cost, supplier reliability and historic delivery performance.
- –Feature Store (MLflow): Helps to manage features from different sources while keeping it consistent during model training and inference. Feature versioning is also tracked by MLflow which can produce reproducible runs.

3.4.4 Fourth Layer - Components of AI Models

The intelligence layer at the core consists of 3 AI models.

- –The demand forecasting LSTM Model is a neural network designed to identify dependencies in demand data over time. The capability to learn long-term patterns and seasonality is an added advantage of LSTMs.
- –The XGBoost Model is a gradient boosting model that has been trained to predict the probability of a late delivery. We are using XGBoost because it has proven to be very efficient with tabular data. Furthermore, XGBoost can handle the class imbalance of the delivery risk prediction (late deliveries).
- –The Inventory Optimization module utilizes outputs from forecast and risk prediction models to calculate

optimal levels, reorder points and order quantities using a mathematical optimization engine.

3.4.5 Fifth Level: Model Serving und APIs (lila).

It makes AI models usable for downstream application, and make it operable.

- –REST APIs (FastAPI): A modern and high-performance API framework for serving predictions. FastAPI is selected due to its high ease of use, automatic documentation and high throughput.
- –Our prediction cache reduces latency of the model and does not put load on it by storing the prediction. For realtime applications wherein the users expect responses quickly this is important.
- –Monitoring deployed models for performance and health. (Prometheus) Tracking metrics including prediction latency, prediction error rate, and model drift helps to catch issues early.

3.4.6 Sixth Layer: Application and Dashboard Orange

This layer offers user-oriented interfaces for different stakeholder groups.

- –It's a React-built app and web application. Its user interface is designed for supply chain planning and management, featuring a responsive design. It provides detailed forecasts, risk alerts, recommendations, and suggested inventory.
- –The Mobile App (React Native) allows managers to access any information in the supply chain and decide on-the-go.
- –Development of Executives Dashboard (Tableau/Power BI) which will provide high-level, dashboard views of key performance metrics and trends.
- –Alert System (Real-time Notifications): Generates early warnings to key stakeholders when critical events arise (e.g., risk of stockout, surge in demand).

3.4.7 Seventh Layer: Decision Support & Outcomes Falling (Pink)

The last layer is the output of the system.

- –Weekly and monthly demand estimations for each product category for better visibility of future demand.
- –Notifications of potential delays enabling early mitigation of the risk.
- –Detailed recommendations for reorder points and order quantities in the inventory, optimized for cost and service level.

We constantly track the performance of the model in terms of its accuracy, service levels and other such metrics

3.5 The flow of information and the feedback cycle

Two important feedback loops are built into the architecture.

1. **Model Retraining Loop (Dotted Line):** The performance metrics generated by Decision Support determine when feature engineering will take place in the Feature Store. As a result, retraining of models periodically needs to be done. The activities continue to be relevant and responsive to business changes.
2. **Monitoring Feedback (Dotted Line):** The information received by the model monitoring system are risk alerts and actual delivery outcome, which helps in identifying model drift that is an area of improvement and can be taken up.

3.6 Crucial Architectural Principles:

- –**Modularity** means that the layers can be modified without interfering with each other (layers can be updated).
- –Scalability: The architecture was built to accommodate growing data sizes and complexity of models.
- –Resilience: Five resilience multiple data sources feedback loops ensure system continuing operations when one system fails though continuity condition inherent networks
- –Transparency: Presenting and explaining the whole functioning of the overall application and its workings in detail.
- –Continuous Improvement: Involving feedback improved their system over time because of monitoring tools in the system.

The best-in-class architecture helps construct an AI-enabled supply chain management system in contemporary times. Providing the systems with more information by integrating multiple data sources and using enhanced feature engineering can help provide business values through a variety of fraud detection, delivery risk reduction and inventory optimization among others.

4 Experimental Setup and Evaluation

The dataset underwent preprocessing to remove NULL values at first. Categorical variables were one-hot encoded. Finally, numerical variables were normalized. Demand forecasting time-series data was aggregated weekly. In case of the forecasting and the classification tasks, the data sets were split into trains (70% of the data) and tests (30% of the data) while keeping the time sequence of the transactions intact. Standard metrics were used to evaluate each model component performance:

–To put it statistically, your coefficients of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to verify the accuracy of your sales. That is, using your coefficients, you will compare your predicted sales with the actual sales in the test set.

–To evaluate the capacity of the predictive model to correctly classify late deliveries, Accuracy, Precision, Recall and F1-Score were derived from the confusion matrix that was generated on the test set.

5 Results

This section presents the experimental results of the proposed model. The performance of each component was evaluated on a hold-out test set, and the outcomes are summarized in the accompanying tables and discussed in detail below.

5.1 Demand Forecasting Performance

To highlight the value addition of AI model, LSTM based demand forecasting model was compared with a conventional statistical model, the Seasonal Autoregressive Integrated Moving Average (SARIMA). In all metrics, the LSTM model in Table 6 performs better than the SARIMA model, showing significantly high accuracy in predicting future sales.

Table 6: Performance Comparison of Demand Forecasting Models

Model	MAE	RMSE	MAPE (%)
SARIMA	45.82	62.14	21.5%
LSTM	28.15	39.47	13.2%

The LSTM model's MAE and RMSE are the least which indicates that the model?s prediction is nearer or closer to the real or actual sales. The MAPE has dropped from 21.5% to 13.2% that is noteworthy from 21.5%-13.2% or an improvement of approximately 38% on forecasting. With greater accuracy comes better decision making for supply chain planners on production planning and inventory allocation, reducing a dual risk of stockout and overstock.

5.2 Delivery Risk Prediction Performance

The evaluation of performance through the confusion matrix and classifier metrics of XGBoost for predicting the risk of late delivery. As demonstrated in Table 7, the model is effective in predicting shipments that are likely to be delayed.

Table 7: Performance of the Delivery Risk Prediction Model (XGBoost)

Metric	Score
Accuracy	0.92
Precision	0.94
Recall	0.91
F1-Score	0.92

An accuracy of 92% means that the model classifies the delivery status correctly for the bulk of the shipments. A precision of 0.94 is extremely useful in practice. This means that if the model predicts a shipment will be late, it will be correct 94% of the time. This enables planners to take proactive action such as speeding up the shipment or notifying the customer without causing too many false alarms. A recall of 0.91 indicates that the model correctly identifies 91% of all late deliveries. Thus, almost all shipments that should be checked are flagged.

5.3 Simulated Impact on Inventory Management

In order to illustrate the practical benefits of the integrated framework, inventory performance was simulated for both a conventional supply chain model and the proposed AI-driven model, enabling a comparative analysis of their effectiveness. This simulation on a product category was for the 52 weeks period. The classical technique used a constant Safety Stock level reliance on historic Demand. Within the AI-driven framework, dynamic stock levels, as determined by the inventory optimization component, were employed to enhance inventory management efficiency.

Table 3 illustrates the performance of the AI-driven model (9 words). The model is based on demand and risk forecast which reduces the average stock level by 23.3% and hence, holding costs. Most notably of all, it reduced the stockout incidents by 83.3%. Consequently, the need for costly expedites declined too. The simulation demonstrates how components of the model can work together to provide beneficial impacts in efficiency and customer service levels. It thereby demonstrates a clear route towards digital empowerment in supply chain planning.

6 Conclusion and Future Work

The aim of study is the design and validation of an AI based a model for the digital empowerment of supply

Table 8: Simulated Inventory Performance Comparison

Metric	Traditional Approach	AI-Driven Approach	Improvement
Average Inventory Level (Units)	1,500	1,150	-23.3%
Stockout Incidents	12	2	-83.3%
Inventory Holding Cost ($)	75,000	57,500	-23.3%
Expediting Costs ($)	18,000	3,000	-83.3%

chains for an enhanced planning system. By get benefits from machine learning for accurate demand forecasting, reliable delivery risk prediction, and efficient inventory management, organizations can enhance their supply chain management systems to be smarter, proactive and more agile. The results obtained from the DataCo Smart Supply Chain dataset provide empirical evidence supporting the effectiveness of the proposed model. The LSTM-based prediction components has improved 38% to traditional methods. The XGBoost-based risk prediction model also identified delivery delays with an accuracy of 94% and recall of 91%. Furthermore, integrating the simulation results from the model shows that there is a potential reduction of the costs of inventory management and improve the service levels. Moreover, there will be a reduction of 83.3% in stockouts and expediting costs.

The results of this study indicates that artificial intelligence is a key factor in the digital transformation of supply chain operations. The model provides planners with accurate forecasts and impartial risk assessments that allow for data-informed decisions to optimize performance in the supply network. This study adds to the literature by proposing a holistic and unified AI framework employed integratively for the components of supply chain planning as opposed to a silos of using AI tools. According to the study, a practical blueprint for applying AI to meet challenges in complexity management to enhance operation efficiency to generate competitive advantage.

The research findings look promising but there are some limitations of this study which can be evaluated further. The model encountered in this study was trained and tested with a large but single dataset. In future research, the proposed model could be applied to additional supply chain datasets to evaluate its generalizability across different industries and geographic regions.

The decision support framework integrated within the inventory optimization software is dynamic in nature. In this context, advanced optimization algorithms can be employed to enhance performance. The application of deep reinforcement learning enables the system to learn optimal inventory policies directly from data, representing a transition from predictive analytics to prescriptive analytics.

Live weather feeds or social media trends are various additional sources of data that could enhance accuracy. These might be examined in future studies. Additionally, customer reviews, supplier communications, and other unstructured data can be leveraged to enhance the performance of the model. The human-in-the-loop aspect of digital empowerment needs more research. Investigation will generally revolve around user interfaces or Dashboards for supply chain planners that present AI-driven insights in an intuitive to use, actionable, and trustworthy way to co-operate humans and machines. In short, as the use of AI technology continues to grow, future studies should examine algorithm bias data privacy as well as the ethical implications and challenges of using AI in supply chain decisions.

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References

[1] Emna Bouazizi, Ayman Khedr, Sherin Elfaioumy, and Mohamed Belal. Inventory optimization using data science technologies for supply chain 4.0. *International Arab Journal of Information Technology (IAJIT)*, 21(6), 2024.
[2] Haoyang Wu, Jing Liu, and Biming Liang. Ai-driven supply chain transformation in industry 5.0: Enhancing resilience and sustainability. *Journal of the Knowledge Economy*, 16(1):3826–3868, 2025.
[3] S. I. S. Mohammad, S. A. Alenazi, B. Al Oraini, H. A. Al-Ababneh, A. S. Al-Adwan, A. Vasudevan, and N. Alshdaifat. Enhancing transparency of blockchain technology in supply chain management. *Applied Mathematics & Information Sciences*, 20(1):13–21, 2026.
[4] Mohammad Shamsuddoha, Eijaz Ahmed Khan, Md Maruf Hossan Chowdhury, and Tasnuba Nasir. Revolutionizing supply chains: unleashing the power of ai-driven intelligent automation and real-time information flow. *Information*, 16(1):26, 2025.
[5] Uche Nweje and Moyosore Taiwo. Leveraging artificial intelligence for predictive supply chain management, focus on how ai-driven tools are revolutionizing demand forecasting and inventory optimization. *International Journal of Science and Research Archive*, 14(1):230–250, 2025.

[6] M. Riad, M. Naimi, and C. Okar. Enhancing supply chain resilience through artificial intelligence. 2024.

[7] P. K. Singh. Digital transformation in supply chain management: Artificial intelligence (ai) and machine learning (ml) as catalysts for value creation. *International Journal of Supply Chain Management*, 12(6):57–63, 2023.

[8] M. Naveena, N. Ellaturu, T. L. Kumari, S. Bambuwala, and M. Rajalakshmi. Ai-driven solutions for supply chain management. *J. Inform. Educ. Res*, 4:861–868, 2024.

[9] K. C. Yarlagadda. Ai-powered supply chain optimization: Enhancing demand forecasting and logistics. *Journal of Computer Science and Technology Studies*, 7(4):792–801, 2025.

[10] H. Rashid. Designing cost-effective, ai-powered demand forecasting models for the manufacturing sector. *Journal of Artificial Intelligence & Cloud Computing*, 3(1):2–5, 2024.

[11] N. Eyo-Udo. Leveraging artificial intelligence for enhanced supply chain optimization. *Open Access Research Journal of Multidisciplinary Studies*, 7(2):1–15, 2024.

[12] A. K. Kalusivalingam, A. Sharma, N. Patel, and V. Singh. Enhancing supply chain resilience through ai: Leveraging deep reinforcement learning and predictive analytics. *International Journal of AI and ML*, 3(9), 2022.

[13] A. Aldoseri, K. Al-Khalifa, and A. Hamouda. A roadmap for integrating automation with process optimization for ai-powered digital transformation. 2023.

[14] E. C. Onukwulu, M. O. Agho, and N. L. Eyo-Udo. Developing a framework for ai-driven optimization of supply chains in energy sector. *Global Journal of Advanced Research and Reviews*, 1(2):82–101, 2023.

[15] E. A. Abaku, T. E. Edunjobi, and A. C. Odimarha. Theoretical approaches to ai in supply chain optimization: Pathways to efficiency and resilience. *International Journal of Science and Technology Research Archive*, 6(1):92–107, 2024.

[16] E. Francis Onotole, T. Ogunyankinnu, Y. Adeoye, A. A. Osunkanmibi, G. Aipoh, and J. Egbemhenghe. The role of generative ai in developing new supply chain strategies: Future trends and innovations. *International Journal of Supply Chain Management*, 11(4):325–338, 2022.

[17] S. Bag, S. Routray, T. Saikouk, and D. Roubaud. Generative ai-powered innovation on data-driven financial decision-making in operations and supply chain management: A moderated mediation analysis. *Information Systems Frontiers*, pages 1–30, 2025.

[18] O. A. Elufioye, C. U. Ike, O. Odeyemi, F. O. Usman, and N. Z. Mhlongo. Ai-driven predictive analytics in agricultural supply chains: A review. *Computer Science & IT Research Journal*, 5(2):473–497, 2024.

[19] S. B. Dhal and D. Kar. Transforming agricultural productivity with ai-driven forecasting: Innovations in food security and supply chain optimization. *Forecasting*, 6(4):925–951, 2024.

[20] E. C. Onukwulu, M. O. Agho, N. L. Eyo-Udo, A. K. Sule, and C. Azubuike. Advances in automation and ai for enhancing supply chain productivity in oil and gas. *International Journal of Research and Innovation in Applied Science*, 9(12):654–687, 2024.

[21] J. Zaman, A. Shoomal, M. Jahanbakht, and D. Ozay. Driving supply chain transformation with iot and ai integration: A dual approach using bibliometric analysis and topic modeling. *IoT*, 6(2):21, 2025.

[22] S. Chauhan, R. Singh, A. Gehlot, S. V. Akram, B. Twala, and N. Priyadarshi. Digitalization of supply chain management with industry 4.0 enabling technologies: A sustainable perspective. *Processes*, 11(1):96, 2022.

[23] S. S. Goswami, S. Mondal, S. Sarkar, K. K. Gupta, S. K. Sahoo, and R. Halder. Artificial intelligence-enabled supply chain management: Unlocking new opportunities and challenges. In *Artificial Intelligence and Applications*, volume 3, pages 110–121. 2025.

[24] H. Wu, G. Li, and H. Zheng. How does digital intelligence technology enhance supply chain resilience? sustainable framework and agenda. *Annals of Operations Research*, pages 1–23, 2024.