ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

Article Info
Date Received: 14 / 03/ 2026
Date Revised: 01/04/2026
Available Online: 18 /04 /2026

ADVANCED DEMAND FORECASTING FOR RETAIL SUPPLY CHAIN MANAGEMENT USING DATA SCIENCE AND MACHINE LEARNING INVENTORY OPTIMIZATION

1.MR.B.V.RAM KUMAR ,2. K.REVATHIPADMA,3. M.TEJAKOTESWARARAO,4. K.MANINDRA,5. M.BHAGYASRI

Author Affiliations

1. Asst.Professor ,Department of Computer Science & Engineering, DNR College of Engineering & Technology, Balusumudi, Bhimavaram -534 202, W.G. Dist , Andhra Pradesh, INDIA.

2,3,4,5.Student ,Department of Computer Science & Engineering, DNR College of Engineering & Technology, Balusumudi, Bhimavaram -534 202, W.G. Dist , Andhra Pradesh, INDIA.

10.5281/zenodo.19641568

ABSTARCT

This project presents an interactive Streamlit-based web application that enables advanced demand forecasting for retail supply chain management using a pre trained XGBoost machine learning model. The main goal is to optimize inventory by accurately predicting daily item-level sales based on features like store ID, item ID, and date attributes (year, month, day, day of week). Users can upload a CSV file containing test data, and the application performs real-time sales predictions using the trained model. The app provides rich visual analytics including monthly sales trends, store and item-specific breakdowns, and actual vs. predicted comparison charts. It also highlights the month with the highest sales and calculates metrics such as Root Mean Square Error (RMSE) when actual sales data is available. Users can download the forecast results as a CSV file for further analysis. The application uses data preprocessing, Seaborn and Matplotlib for plotting, and joblib for loading the XGBoost model efficiently. Through an intuitive interface, it empowers retailers to make data-driven inventory decisions, reduce overstock or understock issues, and enhance operational efficiency

Keywords: Demand Forecasting, Retail Inventory Optimization, Machine Learning (XGBoost), Streamlit Web App, Data Visualization, Predictive Analytics, Root Mean Square Error (RMSE), Real-Time Prediction, Inventory Management

1. INTRODUCTION

1.1 BRIEF INFORMATION

This project focuses on improving demand forecasting in retail supply chain management using Data Science and Machine Learning techniques [3], [5]. In traditional systems, inaccurate demand prediction leads to overstocking or stock shortages, resulting in financial losses and reduced customer satisfaction [4]. The proposed system uses historical sales data to analyze patterns such as trends, seasonality, and customer behavior [18], [17]. Machine learning algorithms are applied to predict future demand with higher accuracy [7], [9]. Based on these predictions, inventory levels are optimized to ensure the right quantity of products is available at the right time [6], [14]. The system helps in reducing excess inventory, avoiding stockouts, and improving overall supply chain efficiency [6]. It enables businesses to make data-driven decisions, reduce operational costs, and increase profitability [3]. This project demonstrates the practical application of machine learning in solving real-world problems in retail and supply chain management [7], [8].

1.2 PURPOSE

The purpose of this project is to develop a demand forecasting system using Data Science and Machine Learning [3], [5]. It analyzes historical sales data to identify patterns like trends and seasonality [18]. The system predicts future product demand with improved accuracy [7], [9]. Based on predictions, it helps optimize inventory levels to avoid overstock and shortages [6]. It improves supply chain efficiency and supports data-driven decision-making [3].

1.3 MOTIVATION

The challenges faced in retail supply chain management [15]. Inaccurate demand forecasting often leads to overstocking or stock shortages [4]. These issues result in financial losses and poor customer satisfaction [4]. Traditional forecasting methods are not efficient in handling complex data patterns [3]. Advancements in Data Science and Machine Learning provide better prediction capabilities [7], [9]. This project aims to use these technologies to improve forecasting accuracy and inventory management [5].

1.4 PROBLEM STATEMENT

Retail businesses face difficulty in accurately predicting customer demand [3]. Poor demand forecasting leads to overstocking or stock shortages [4]. This results in increased operational costs and loss of revenue [6]. Traditional methods fail to capture complex patterns like seasonality and trends [17], [18]. Lack of data-driven decision-making affects supply chain efficiency [5]. There is a need for a system that uses machine learning to improve demand prediction and inventory optimization [7], [9].

2. LITERATURE REVIEW

Various studies have proposed data-driven approaches to improve demand forecasting in retail supply chain management [3], [5]. Traditional statistical models such as time series analysis and regression methods have been widely used for predicting demand, but they often fail to capture complex patterns in large datasets [17], [18].

2.1 Demand Forecasting Challenges in Retail
AUTHORS: Makridakis, S., Wheelwright, S.C., Hyndman ,R.J.

Demand forecasting in retail is a complex task due to factors such as seasonal variations, changing customer preferences, and market uncertainties [3], [15]. Traditional forecasting methods often fail to handle these dynamic conditions effectively [17].

Inaccurate predictions can lead to overstocking or stock shortages, resulting in financial losses and reduced customer satisfaction [4]. Studies highlight that incorporating advanced analytics and machine learning techniques can significantly improve forecasting accuracy [7], [9]. By analyzing large volumes of historical data, these approaches help identify hidden patterns and trends, enabling better decision making in supply chain management.

2.2 Data-Driven Approaches in Supply Chain Management
AUTHORS: Christopher, M., Lee, H.L.,

Data-driven approaches play a crucial role in modern supply chain management by enabling accurate analysis and decision-making [5]. Traditional supply chain systems relied on manual estimation and limited data, leading to inefficiencies [3], which often led to inefficiencies and delays. With the growth of big data and analytics, organizations can process large volumes of historical and real-time data [1]. These approaches help identify demand patterns and optimize inventory levels [5]. These approaches help in identifying demand patterns, improving forecasting accuracy, and optimizing inventory levels. Studies show that integrating data science techniques into supply chain operations enhances visibility, reduces uncertainty, and improves overall efficiency. This has led to the adoption of intelligent systems that support better planning and resource utilization.

2.3 Time series Forecasting in Retail
AUTHORS: Rob J.Hyndman ,George Athanasopoulos

Time series forecasting techniques such as ARIMA and Exponential Smoothing have been widely used in retail demand prediction [17], [18]. These methods analyze historical data to identify trends and seasonal patterns [18]. However, they have limitations in handling large-scale and complex datasets with multiple influencing factors [3]. Despite this, they provide a strong baseline for comparison with modern machine learning approaches

2.4 Machine Learning Models for Demand Prediction

AUTHORS: Leo Breiman,Vladimir Vapnik

Machine learning models like Random Forest and Support Vector Machines improve demand forecasting accuracy [7]. These models capture non-linear relationships and utilize multiple features such as sales and customer behavior [5]. They outperform traditional statistical methods [3].

2.5 Deep Learning Approaches in Supply Chain

AUTHORS: Yann Lecun, Yoshua Bengio, Geoffrey Hinton

Deep learning techniques such as LSTM networks are increasingly used for demand forecasting [7], [8]. These models learn complex patterns and long-term dependencies in data [9].

Their application improves forecasting precision and inventory planning [5].

2.6 Inventory Optimization Techniques

AUTHORS: Harris,F.W.

Inventory optimization methods such as the Economic Order Quantity (EOQ) model help determine the optimal stock level to minimize costs. When combined with machine learning-based demand forecasts, these techniques significantly improve inventory management. They help reduce holding costs, avoid stockouts, and ensure efficient utilization of resources.

3. PROPOSED SYSTEM

The proposed system uses data science and machine learning techniques to improve demand forecasting. It analyzes historical sales data to identify patterns such as trends and seasonality. Machine learning models are used to predict future demand with higher accuracy.Based on predictions, the system optimizes inventory levels to improve efficiency and reduce losses.

ADVANTAGES OF PROPOSED SYSTEM:

1. Provides more accurate demand forecasting using machine learning reducing overstocking and stock shortage.
2. Improves inventory management and overall supply chain efficiency, leading to reduced costs and better decision-making.

3.1 System Architecture

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

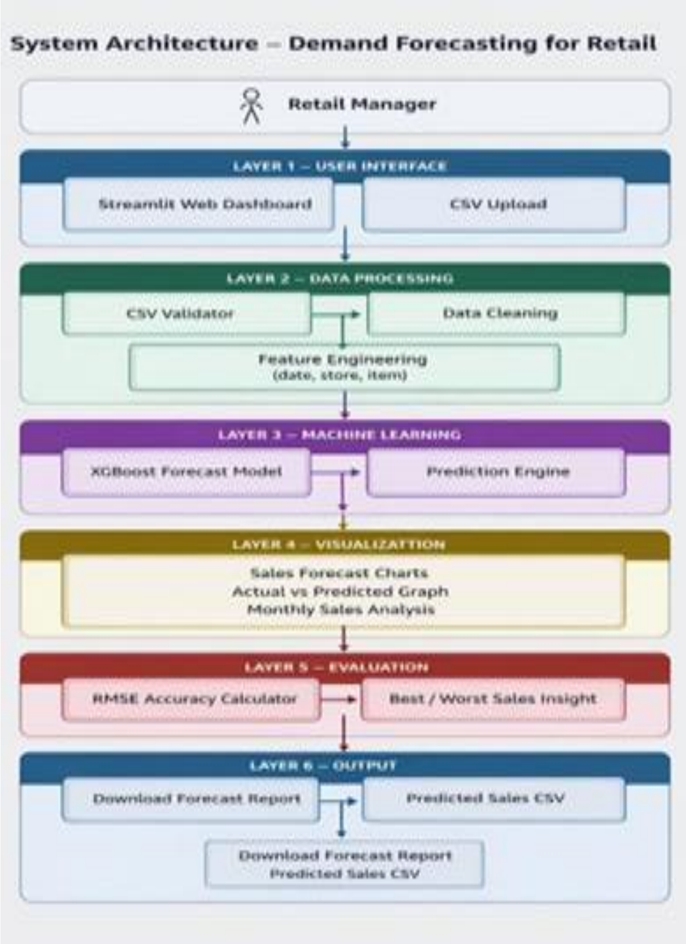


Fig 1: System Architecture

3.2 Use case Diagram

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

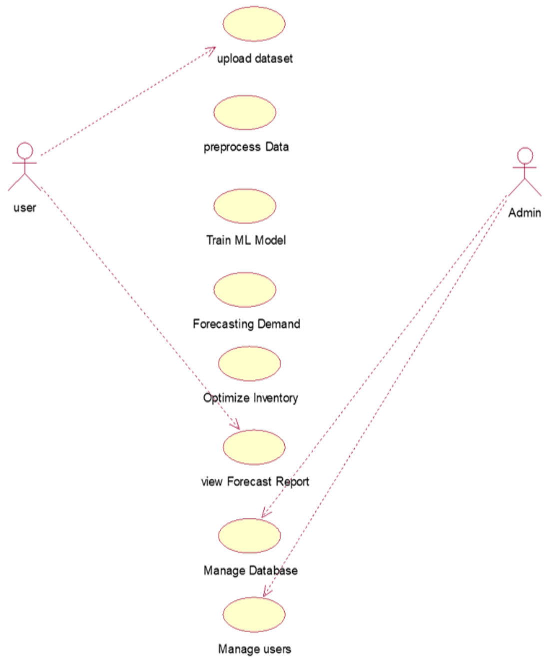
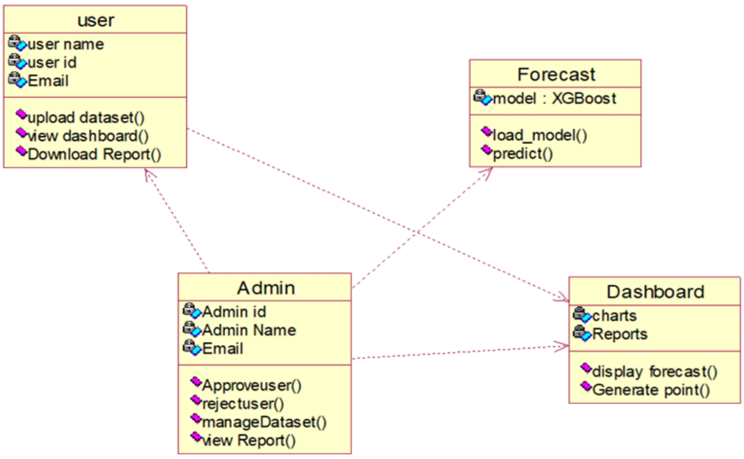


Fig 2: Use Case Diagram

3.3 Class Diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain

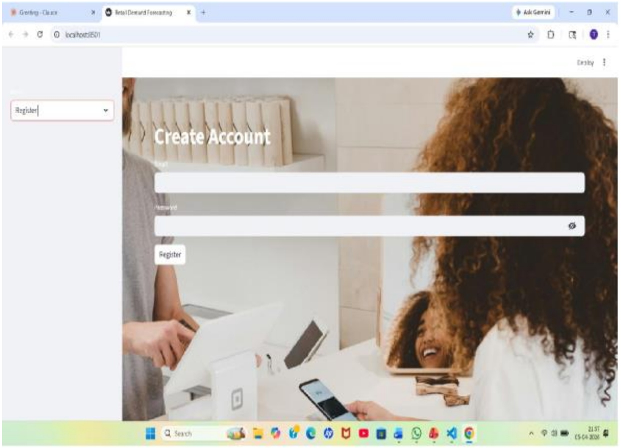


"attributes" that uniquely identify the class.

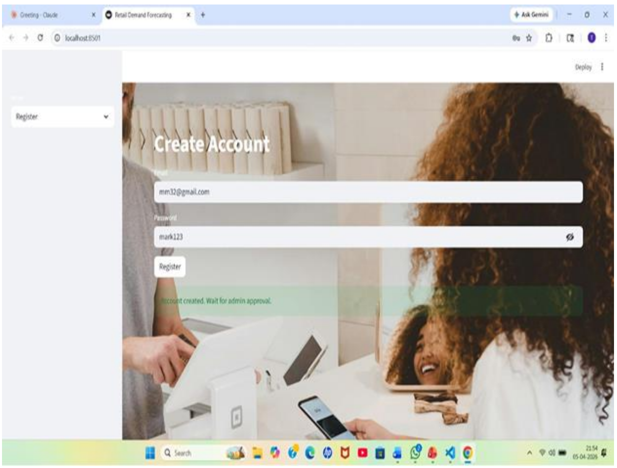
Fig 3: Class Diagram

4. RESULTS

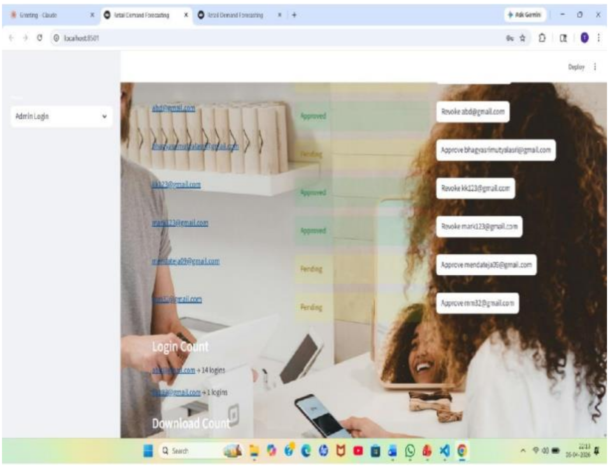
HOME PAGE



USER REGISTRATION

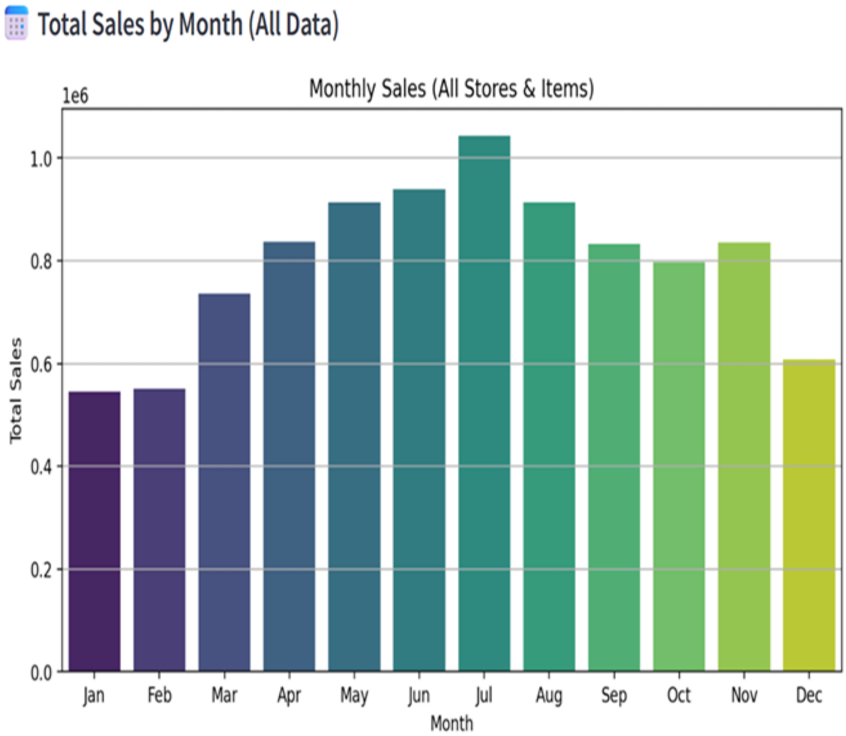


ADMIN MANAGING DETAILS:



ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

FINAL OUTPUT AFTER DATA UPLOADED:



5. CONCLUSION

In this project, we successfully developed and implemented an advanced demand forecasting system tailored for the retail supply chain using machine learning and interactive data visualization. The core objective was to address the limitations of traditional forecasting methods by building a data-driven, intelligent, and user-friendly application capable of predicting daily item-level sales with high accuracy. Through the use of a pre-trained XGBoost model and a well-designed Streamlit interface, the system achieves its goal of empowering retail stakeholders to make better, faster, and more informed decisions regarding inventory management and demand planning.The project successfully demonstrates how machine learning can be applied to improve demand forecasting in retail supply chains. Multiple models, including Linear Regression, Decision Tree, Random Forest, and XGBoost, were implemented and evaluated, with XGBoost providing the most accurate predictions based on lower RMSE values.By using these predictions, the system enables better inventory planning through optimized stock levels, reducing the risks of overstocking and stockouts. This leads to improved operational efficiency and cost savings for retail businesses.

The project highlights the importance of data-driven decision-making in modern supply chain management. However, the accuracy of predictions depends on the quality and variety of input data, such as seasonal trends and external factors.In future improvements, the system can be enhanced by integrating real-time data, advanced time-series models, and automated inventory control mechanisms to make it more practical and scalable for real-world applications.This project demonstrates the effectiveness of machine learning models in predicting retail demand with improved accuracy. Among the implemented models, XGBoost outperformed others in terms of RMSE, proving its strength in handling complex patterns in sales data.The integration of demand forecasting with inventory decision-making ensures better stock control by estimating reorder levels and maintaining safety stock. This reduces operational inefficiencies and enhances supply chain performance.

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

Overall, the system provides a scalable and data-driven approach for retail businesses to optimize inventory and improve profitability.The developed system provides a practical solution for retail businesses facing demand uncertainty and inventory mismanagement. By leveraging machine learning, the project helps in making accurate demand predictions, leading to better stock planning and reduced losses. The use of optimized inventory strategies ensures that products are available when needed while avoiding unnecessary storage costs. This directly contributes to improved customer satisfaction and increased business efficiency.

6. FUTURE SCOPE

While the current system demonstrates high performance and usability in retail demand forecasting, there remains significant potential for enhancement and expansion. The future scope of this project includes both technical and functional improvements aimed at increasing forecasting precision, system automation, integration, and business adaptability.

1. **Real-Time Forecasting Integration:**
   Currently, the system works with batch data uploads in CSV format. Future upgrades could incorporate real-time data streams using APIs connected to Point-of-Sale (POS) systems or ERP software. This would allow the model to forecast on a rolling basis and adjust inventory recommendations dynamically based on live transactions.

2. **wMulti-Model Hybrid Forecasting:**
   The system currently utilizes XGBoost for its predictive capabilities. However, combining this with deep learning models like LSTM, GRU, or Transformer-based time series models could improve performance, especially for long-range forecasting. A hybrid architecture may also capture seasonal, promotional, and trend-based patterns more effectively.

3. **Incorporation of External Variables:**
   Future versions of the model could integrate additional data sources such as weather conditions, holidays, promotions, pricing changes, competitor activity, or even social media sentiment. These variables are known to significantly affect consumer demand, and incorporating them could make the system even more robust and context-aware.

4. **Autonomous Inventory Optimization (Reinforcement Learning):**
   Extending the model to not only forecast demand but also recommend optimized inventory decisions (how much to restock, when to restock) using reinforcement learning techniques would make the system an end-to-end intelligent inventory assistant. This would transition the tool from predictive to prescriptive analytics.

5. **Multi-Echelon Supply Chain Support:**
   Future iterations could expand the forecasting capabilities across multiple supply chain levels — suppliers, warehouses, distributors, and retail stores. This multi-echelon visibility would empower centralized decision-making, ensuring synchronization across the entire supply chain network.

6. **Cloud Deployment and Scalability:**

ISSN: 2582 - 6379
IJISEA Publications
International Journal for Interdisciplinary Sciences and Engineering Applications
IJISEA - An International Peer- Reviewed Journal
2026, Volume 7 Issue 2
www.ijisea.org

The current application runs locally or in a limited environment. Deploying it on a cloud platform like AWS, Azure, or Google Cloud would enhance accessibility, scalability, and enable enterprise-wide use. It could also support multi-user access, role-based dashboards, and centralized data storage.

7. **User Role Management and Dashboarding:**
   Implementing role-based access (e.g., store manager, regional planner, executive) and customizable dashboards would personalize the forecasting insights and enhance usability across different business functions. Each user could access relevant KPIs and reports based on their responsibilities.

8. **Model Monitoring and Auto-Retraining:**
   As data patterns evolve over time, the model may need retraining. A future enhancement could include automated model evaluation and retraining pipelines to ensure continued accuracy and adaptability to changing market conditions.

9. **Mobile App and Responsive Design:**
   Developing a lightweight mobile version or ensuring full responsiveness of the existing Streamlit UI could allow supply chain professionals to access forecasts and insights on-the-go, improving decision-making speed and flexibility.

10. **Explainable AI (XAI) Features:**
    Integrating tools like SHAP (SHapley Additive exPlanations) or LIME to explain predictions can help users understand which features (e.g., day of week, item type, season) are most influential in driving demand, increasing transparency and trust in the system.

REFERENCES

1. Chui, M.; Issler, M.; Roberts, R.; Yee, L. Technology Trends Outlook 2023; McKinsey & Company: New York, NY, USA, 2023.

2. Amed, I.; Balchandani, A.; Berg, A.; Hedrich, S.; Jensen, J.E.; Le Merle, L.; Rölkens, F. State of Fashion 2022: An Uneven Recovery and New Frontiers; Mckinsey & Company: New York, NY, USA, 2021.

3. Fildes, R.; Ma, S.; Kolassa, S. Retail forecasting: Research and practice. Int. J. Forecast. 2022, 38, 1283 1318. [CrossRef]

4. Trapero, J.R.; Kourentzes, N.; Fildes, R. On the identification of sales forecasting models in the presence of promotions. J. Oper. Res. Soc. 2015, 66, 299–307. [CrossRef]

5. Ma, S.; Fildes, R.; Huang, T. Demand forecasting with high dimensional data: The case of SKU retail sales forecasting with intra-and inter-category promotional information. Eur. J. Oper. Res. 2016, 249, 245 257. [CrossRef]

6. Chen, X.; Hu, P.; Hu, Z. Joint pricing and inventory decisions. In Research Handbook on Inventory Management; Edward Elgar: London, UK, 2023; pp. 288–306.

7. Bandara, K.; Bergmeir, C.; Hewamalage, H. LSTM-MSNet: Leveraging forecasts on sets of related time series with multiple seasonal patterns. IEEE Trans. Neural Netw. Learn. Syst. 2020, 32, 1586–1599. [CrossRef]

8. Wen, R.; Torkkola, K.; Narayanaswamy, B.; Madeka, D. A multi-horizon quantile recurrent forecaster. arXiv 2017, arXiv:1711.11053.

9. Oreshkin, B.N.; Carpov, D.; Chapados, N.; Bengio, Y. N-BEATS: Neural basis expansion analysis for interpretable time series forecasting. arXiv 2019, arXiv:1905.10437.

10. Gronauer, S.; Diepold, K. Multi-agent deep reinforcement learning: A survey. Artif. Intell. Rev. 2022, 55, 895–943. [CrossRef]

11. Zadro, F. Utilizing Reinforcement Learning for Decision Management in B2B Cus-tomer Relationship Management Envi-ronments. Ph.D. Thesis, University of Applied Sciences Technikum Wien, Vienna, Austria, 2020.

12. D'Souza, S. Implementing reinforcement learning algorithms in retail supply chains with OpenAI gym toolkit. arXiv 2021, arXiv:2104.14398.

13. Liu, X.; Hu, M.; Peng, Y.; Yang, Y. Multi-agent deep reinforcement learning for multi-echelon inventory management. Prod. Oper. Manag. 2022, 10591478241305863. [CrossRef]

14. Bensoussan, A.; Xie, Y.; Yan, H. Joint inventory-pricing optimization with general demands: An alternative approach for concavity preservation. Prod. Oper. Manag. 2019, 28, 2390–2404. [CrossRef]

15. McCormick, H.; Cartwright, J.; Perry, P.; Barnes, L.; Lynch, S.; Ball, G. Fashion retailing–past, present and future. Text. Prog. 2014, 46, 227–321. [CrossRef]

16. Chen, Y.; Song, G.; Ye, Z.; Jiang, X. Scalable and transferable reinforcement learning for multi-agent mixed cooperative–competitive environments based on hierarchical graph attention. Entropy 2022, 24, 563. [CrossRef]

17. Gardner, E.S., Jr. Exponential smoothing: The state of the art—Part II. Int. J. Forecast. 2006, 22, 637 666. [CrossRef]

18. Hyndman, R. Forecasting: Principles and Practice; OTexts: Melbourne, Australia, 2018.

19. Durbin, J.; Koopman, S.J. Time Series Analysis by State Space Methods; Oxford University Press: Oxford, UK, 2012; Volume 38.

20. Munim, Z.H. State-space TBATS model for container freight rate forecasting with improved accuracy. Marit. Transp. Res. 2022, 3, 100057. [CrossRef]