UNDER PEER REVIEW

Data Science for Demand Forecasting and Inventory Management: A Comprehensive Review

***Abstract*—Both demand forecasting and inventory management are essential in supply chain management; however, traditional techniques face challenges in dealing with variability of the contemporary markets. In this review, the authors discuss how data science has revolutionised these fields, using techniques such as ARIMA, LSTM networks, hybrid models and machine learning algorithms. Demand planning and management is improved through the use of predictive analytics because it includes historical data, external factors and real time information. Examples from various industries show the implementation of external factors like seasonality, macroeconomic factors, and disruptions into the forecasting process, thus enhancing flexibility and robustness. However, issues such as data quality, scalability, and interpretability still remain, and demand collaboration between fields and the use of novel techniques such as federated learning and quantum computing. In this paper, integrating the existing practices and the future trends, the authors offer a roadmap for researchers and practitioners to fully unlock the power of data science for supply chain transformation.**

Keywords: *Demand forecasting, inventory management, predictive analytics, machine learning, supply chain optimization*

I. INTRODUCTION

Demand forecasting and inventory management are now key elements of supply chain management affecting the overall effectiveness, financial return, and sustainability of a business venture. In the past, these domains have used techniques such as economic order quantity models and basic trend extrapolation that do not cope with the additional challenges posed by the modern supply chain. However, recent advancements in data processing and storage have made it easy for data science to improve the demand forecasting and make it applicable to SMEs [1]. Notably, approximately 126% of organizations that use consumer analytics allegedly generate a substantial amount of value that is higher than that of competitors, proving the effectiveness of data-driven strategies [2].

However, these conventional approaches provide basic information, and due to their limitations in capturing or handling change in the market and big data, they are not efficient. The new methods of data analysis, including machine learning, time series prediction and data mining, offer increased accuracy and flexibility. For instance, the ARIMA, LSTM networks, and hybrid models have shown promising results in determining patterns from the previous sales data and forecasting future demand patterns [3]. Such improvements do not only help to forecast demand accurately but also work to manage inventory effectively, which results in cutting on costs of holding excess or inadequate stock.

In addition, predictive analytics has transformed inventory management through incorporating dynamic decision making processes. In the current world, machine learning algorithms enable the tracking and control of inventory policies in real-time while taking into consideration factors such as seasonal variation and market shifts [4]. However, some problems like the low quality of data, the issue of scale, and the cross-disciplinary integration are still there. The objective of this paper is to review contemporary data science practices in demand forecasting and inventory management, and discuss success stories, issues, and possibilities of future advancements.This review not only identifies the current state of knowledge but also outlines the future directions to unlock the potential of data science to revolutionise supply chain management.ness. Historically, these domains have relied on traditional approaches like economic order quantity models and basic trend extrapolation, which struggle to address the complexities introduced by modern supply chains. However, due to rapid advancements in data processing and storage, data science has made demand forecasting accessible to businesses of all sizes, empowering even small and medium-sized enterprises (SMEs) to harness data analytics for improving demand forecasting and inventory management strategies [1]. Interestingly, about 126% of businesses leveraging consumer analytics reportedly outperform competitors significantly, showcasing the transformative potential of data-driven approaches [2].

While traditional methods offer foundational insights, their inability to accommodate dynamic market changes and large datasets often leads to inefficiencies. Modern data science techniques, such as machine learning, time-series forecasting, and data mining, provide enhanced accuracy and adaptability. Predictive models like ARIMA, LSTM networks, and hybrid methods have shown promise in identifying patterns from historical sales data and predicting future demand trends [3]. These advancements not only enable precise demand estimation but also optimize inventory levels, reducing costs associated with overstocking or stockouts.

Furthermore, predictive analytics has redefined inventory management by integrating dynamic decision-making processes. Machine learning algorithms now allow real-time monitoring and adjustment of inventory policies, incorporating external factors such as seasonality and market trends [4]. Despite these advancements, challenges such as poor data quality, computational scalability, and the need for interdisciplinary integration persist. This paper aims to explore state-of-the-art data science applications in demand forecasting and inventory management, highlighting real-world successes, challenges, and opportunities for future innovation. By synthesizing existing research and presenting emerging trends, this review provides a comprehensive guide to harness the power of data science in transforming supply chain practices.

II. ADVANCED DATA SCIENCE TECHNIQUES FOR DEMAND FORECASTING

A. Time-Series Analysis for Demand Prediction

Time-series analysis has long been the cornerstone of demand forecasting, with traditional methods like ARIMA (AutoRegressive Integrated Moving Average) and exponential smoothing providing reliable results for linear and stationary data patterns. These models excel in simplicity and interpretability, making them suitable for applications where historical trends and seasonality dominate like the supply chain industry. However, their limitations become evident in complex, dynamic datasets where nonlinearities and external variables significantly influence outcomes. Hybrid models have emerged to address these challenges, combining the strengths of traditional time-series techniques with machine learning (ML) methods [5].

The efficacy of a hybrid ARIMA-SVM (Support Vector Machine) model in predicting stock prices was demonstrated in [6] where the model achieved superior accuracy by capturing both linear and nonlinear components. Similarly, [7] extended this approach by integrating ARIMA with Artificial Neural Networks (ANNs) to enhance retail sales forecasting. These models were exposing the benefits of combining time-series methodologies with advanced algorithms to improve forecast precision. Additionally, incorporating external variables, such as weather or economic indicators, has proven valuable. In a bid to sow that there was a need for a model tailored to the specific situation, [8] developed a random coefficient model which revealed that location-specific weather conditions could influence sales by up to 40.7%.

Despite these advancements, traditional time-series techniques often struggle with scalability and computational demands when applied to real-time, large-scale datasets. However, the inclusion of contextual variables and hybridization with ML techniques addresses some of these limitations, but these approaches require significant preprocessing and domain expertise to implement effectively.

B. *Machine Learning and AI-Driven Forecasting Models*

Machine learning (ML) and artificial intelligence (AI) have revolutionized demand forecasting by introducing robust, flexible, and adaptive models capable of handling complex and high-dimensional datasets through techniques such as ensemble learning, regression models, and convolutional and recurrent neural networks which have emerged as superior alternatives to classical time-series methods. While reiterating that there is not a one size fits all model for forecasting and demand, [1] compared traditional forecasting models with ML approaches and found ensemble methods like XGBoost to significantly outperform classical methods in terms of accuracy and error metrics (RMSE of 55.77 and MAPE of 41.18).

Deep learning models, particularly convolutional LSTMs (ConvLSTMs), have also shown promise in extracting spatiotemporal features, as evidenced in [10], electrification of transport has been a breakthrough in the goal towards a sustainable and eco-friendly world. The challenges lie in distribution and management and to that end, a ConvLSTM was applied to energy demand forecasting which led to impressive results. These models were especially effective in scenarios where data exhibits both spatial and temporal dependencies, such as in energy and logistics sectors. Hybrid models further enhance accuracy by combining the strengths of multiple algorithms. This was evident in [11] where a deep learning approach that integrated LSTMs with Random Forest was developed, effectively modeling complex temporal and regression relationships while ranking explanatory variables by significance.

Furthermore, the transformative potential of ML and AI have been revealed. In a study by [12] on container throughput forecasting using LSTM networks, there was a demonstration of high accuracy, emphasizing the utility of such models in supply chain optimization. In the retail industry, [13] addressed challenges like promotions and competitor actions by integrating ML-driven dynamic adjustment models, significantly improving forecast reliability and showing without a benefit of doubt that "forecasting retail sales can be accomplished with a high degree of accuracy." Similarly, using Rue La La as a case study, [14] leverged a nonparametric structure for their demand prediction model which showed that the implementation of ML algorithms not only optimized inventory but also aligned pricing strategies to consumer demand the test group having a revenue increase by approximately 9.7% and an associated 90% confidence interval of [2.3%, 17.8%].

Despite their advantages, ML and AI models come with challenges, including computational demands, data quality issues, and the need for significant expertise in model development and tuning. These hurdles are particularly evident in SMEs, where access to high-quality data and computational resources is limited [9]. Emerging trends like federated learning and automated machine learning (AutoML) offer potential solutions by democratizing access to advanced forecasting tools while maintaining data privacy and reducing computational overhead.

III. INVENTORY OPTIMIZATION USING PREDICTIVE MODELS

Cost efficiency, customer satisfaction, and operational agility remains the goal of every business as this gives them a competitive edge. To do this, businesses need to optimize their inventories [15],[16]. While traditional methods like the Economic Order Quantity (EOQ) model have historically guided inventory practices, their static assumptions often fail in the face of dynamic market conditions, demand variability, and supply chain complexity. Predictive analytics, on the other hand, has emerged as a transformative solution, leveraging historical data, machine learning algorithms, and real-time insights to address these challenges comprehensively.

A. Traditional Methods vs. Predictive Analytics

Traditional inventory management relies heavily on fixed parameters and simplistic calculations, such as EOQ, safety stock levels, and reorder points. While these approaches offer foundational value, they are constrained by their inability to adapt dynamically to fluctuating demand or supply chain disruptions. EOQ, for instance assumes constant demand and lead times, which rarely align with modern business realities [17]. This rigidity often leads to overstocking, resulting in high holding costs, or stockouts, compromising customer satisfaction and sales [18].

Predictive analytics, by contrast, employs advanced statistical and machine learning techniques to anticipate demand patterns and inventory requirements. [19] highlight how predictive analytics enables businesses to dynamically forecast demand by analyzing historical sales data, external factors such as seasonality, and promotional impacts. This approach not only reduces costs but also aligns inventory levels more closely with real-time market needs. A case study by [20] exemplifies this, where a gradient boosting model accurately classified inventory status (understock, normal, overstock) for a large FMCG company in Indonesia, achieving classification accuracies of up to 84% for certain product categories. Such precision reduces waste and enhances responsiveness. Moreover, it would also be efficient in guiding inventory replenishment.

B. Inventory Replenishment Strategies Using Predictive Models

Predictive analytics also revolutionizes replenishment strategies by integrating forecasting with optimization algorithms. Traditional replenishment strategies often rely on predefined reorder points or manual adjustments, which may not account for real-time variables like sudden demand surges or supply chain delays. Modern predictive approaches incorporate machine learning algorithms, such as reinforcement learning and gradient boosting, to refine replenishment schedules dynamically [21],[22].

In [20], the researcher demonstrated how predictive models, coupled with a visualization dashboard, streamlined inventory decision-making for an FMCG company managing diverse product lines. The use of heatmaps and line graphs provided actionable insights, enabling targeted interventions for understocked or overstocked categories. Similarly, [23] showed the importance of inventory optimization in reducing costs, enhancing cash flow, and mitigating risks. By simulating demand fluctuations and supply chain disruptions, predictive models have been proven to facilitate robust scenario planning and risk management, empowering businesses to maintain agility in volatile markets.

Furthermore, advanced replenishment strategies integrate external variables, such as macroeconomic indicators, supplier reliability, and transportation constraints, to optimize inventory flows [24]. Predictive models can adjust reorder quantities dynamically based on lead time variability or market trends, ensuring that businesses avoid excess inventory while maintaining adequate stock levels. This adaptability fosters resilience, particularly in industries with short product lifecycles or perishable goods.

Unfortunately, despite its transformative potential, predictive analytics in inventory management is not without challenges. As highlighted by [19], the integration of predictive models demands high-quality data and seamless data pipelines, both of which are often lacking in traditional setups. Moreover, [20] notes that while predictive models like gradient boosting deliver impressive accuracy, their interpretability and complexity pose barriers for widespread adoption. To bridge these gaps, businesses must invest in user-friendly interfaces, training, and cross-functional collaboration to maximize the utility of predictive insights. Whilst this is being done, due to the rapid change in the world, businesses would benefit from putting external factors into consideration while forecasting for optimisation.

IV. THE ROLE OF EXTERNAL FACTORS IN FORECASTING AND OPTIMIZATION

The integration of external factors into forecasting and optimization processes represents a critical advancement in adapting predictive models to real-world variability. Traditional time-series forecasting methods, such as ARIMA and exponential smoothing, focus primarily on historical patterns [25]. While effective for stationary trends, these methods falter when external influences, like market shocks or seasonal changes, significantly affect demand. The inclusion of external factors, such as economic conditions, weather, or social events, enhances model robustness and provides actionable insights across diverse applications, from public transportation to supply chain management.

A. Incorporating Seasonality into Demand Forecasting

Seasonal variations remain a major driver of demand fluctuations in industries like retail, agriculture, and transportation [26]. Traditional approaches often struggle to disentangle these periodic patterns from broader trends. [27] demonstrated the utility of models such as ARIMA with Fourier terms and TBATS in addressing seasonality, offering interpretable alternatives to machine learning methods while maintaining comparable accuracy. These methods are particularly valuable for businesses with limited access to advanced computational infrastructure, emphasizing adaptability under constraints. For instance, time-series decomposition coupled with external data, such as holiday schedules or weather changes, provides nuanced forecasts that better capture consumer behavior during peak seasons.

The case study on subway passenger flow forecasting by [28] is an example of the transformative impact of incorporating external factors. Their multi-type attention-based network integrates historical data with real-time station and environmental variables, significantly outperforming traditional baselines. By visualizing the influence of external factors, this approach supports targeted decision-making, such as reallocating resources during festivals or weather-induced surges. This hierarchical integration of seasonal and external inputs underscores the potential for multi-dimensional modeling in addressing complex seasonal dynamics.

B. Market Trends and Macroeconomic Indicators

Incorporating macroeconomic variables into predictive models bridges the gap between localized data patterns and broader market dynamics. For instance, inflation rates, consumer sentiment, and commodity price fluctuations often alter demand in ways that historical data alone cannot predict. [25] went further to highlight the shortcomings of traditional pattern-based models like ARIMA and LSTM when faced with such external shocks. The integration of external variables using machine learning-based black-box models showed significant improvement in forecasting Ethereum prices, balancing precision and interpretability.

Further, the application of external factors in public transportation forecasting, as discussed by [29] further emphasizes their versatility. By leveraging data on weather, holidays, and cultural events, neural networks achieved forecasts with a median absolute error of approximately 4.16, ensuring 80% of predictions remained within an acceptable tolerance range. This integration allowed for proactive adjustments, such as deploying additional buses during inclement weather, enhancing both efficiency and customer satisfaction.

C. Adapting to Uncertainty and Disruptions

The increasing frequency of disruptive events, such as pandemics, geopolitical tensions, and natural disasters, has necessitated the need for complex and adaptive forecasting models. Scenario-based and robust optimization techniques enable businesses to prepare for extreme variability by simulating potential disruptions and their cascading effects on supply chains. [28] utilized attention mechanisms in their subway forecasting model to dynamically adapt to shifts in passenger behavior due to external disruptions, offering a template for resilience in demand forecasting. By visualizing the impacts of various scenarios, such models equip planners to anticipate and respond to crises effectively.

Furthermore, the application of predictive models to high-stakes scenarios, such as the demand for medical supplies during COVID-19, highlights the critical role of external factors in ensuring continuity

[30]. Machine learning techniques, particularly those that incorporate real-time global data, can model disruption-induced demand surges, such as personal protective equipment requirements. The ability to seamlessly incorporate non-traditional factors, such as pandemic case trends or international trade policies, ensures a level of adaptability unmatched by static models.

Case studies across different domains illuminate the practical advantages of external factor integration. From [25] Ethereum price forecasting, which reduced prediction error by incorporating market-driven variables, to [28] subway model that adapted to hierarchical data complexities, the evidence for enhanced predictive capabilities is compelling. Similarly, [29] work in public transportation demonstrated how real-world outcomes, such as reduced overcrowding and delays, stem from meticulous external data incorporation. These examples collectively underscore the value of external factor inclusion in bridging the gap between theoretical forecasting and practical optimization. All of these point to one thing; by strategically incorporating external influences, modern forecasting and optimization models transition from static tools to dynamic systems capable of responding to the complexities of real-world operations. As industries grow more reliant on predictive analytics, the fusion of internal and external variables will remain central to innovation and resilience in decision-making.

V. CHALLENGES AND FUTURE DIRECTIONS

A. Data Quality and Integration Challenges

One of the most persistent barriers to effective demand forecasting and inventory management lies in the quality and integration of data. Fragmented data systems, inconsistent formats, and missing values limit the reliability of predictive models [31]. Siloed systems exacerbate these challenges by hindering cross-functional data sharing, leading to gaps in analysis and decision-making. Preprocessing techniques such as imputation, normalization, and anomaly detection are essential but often labor-intensive, requiring significant domain expertise to execute effectively [32]. Data pipelines, automated tools that standardize and integrate disparate data sources, offer a potential solution. A feasible option is the deployment of cloud-based data lakes that can centralize information while facilitating real-time updates, improving both accessibility and consistency. However, [33] argue that implementing such systems is resource-intensive, presenting a particular challenge for small and medium enterprises (SMEs) that lack the capital or expertise for such investments.

B. Scalability and Real-Time Implementation

Scaling predictive analytics to handle large datasets and real-time demands is another critical challenge, particularly for businesses operating in dynamic environments. Traditional systems often falter under the computational load of processing high-velocity, high-volume data streams. Emerging technologies like distributed computing and edge analytics are addressing this bottleneck. Cloud platforms such as AWS and Azure enable scalable, on-demand computational power, while tools like Apache Kafka facilitate real-time data streaming. However, these technologies require robust infrastructure and skilled personnel for effective deployment [34]. Additionally, achieving real-time implementation necessitates low-latency algorithms, which can be computationally expensive and may compromise model accuracy [35]. Interestingly, all of these challenges guide future research opportunities and model development trends. Developing hybrid systems that balance scalability, accuracy, and cost-effectiveness is an example of such research direction.

C. Ethical Considerations and Model Interpretability

As reliance on AI-driven decision-making grows, ethical concerns around bias, transparency, and accountability have come to the forefront. Predictive models often inherit biases from training data, leading to skewed outcomes that can disadvantage certain groups or regions [36]. However, Explainable AI (XAI) is an emerging field aimed at making complex models more interpretable, thereby enhancing trust and enabling better oversight [37]. Sadly, achieving interpretability often involves trade-offs with model complexity and accuracy, presenting a dilemma for researchers and practitioners alike [38]. Going forward, addressing these issues will require not only technical innovation but also the establishment of robust regulatory frameworks.

D. *Emerging Trends and Research Opportunities*

The landscape of predictive analytics is rapidly evolving, with emerging trends offering solutions to longstanding challenges and opportunities for innovation. Federated learning, which allows decentralized data training while maintaining privacy, is gaining traction as a means of overcoming data-sharing constraints in collaborative environments. This approach is particularly relevant for global supply chains, where data sensitivity often inhibits cross-organization collaboration. Quantum computing, though still in its infancy, promises to revolutionize optimization problems, such as multi-echelon inventory management, by solving them exponentially faster than classical methods. While speculative, early research suggests quantum algorithms could enable real-time, large-scale decision-making even in highly complex systems.

Another promising avenue is the adoption of multi-agent systems, which simulate the interactions between various supply chain entities to optimize outcomes collectively. By integrating behavioral economics and systems thinking, researchers are also exploring the human factors influencing inventory management, such as decision biases and organizational dynamics. Interdisciplinary approaches that combine machine learning with social sciences can address these nuanced challenges, offering a more holistic understanding of supply chain dynamics.

VI. CONCLUSION

This review focuses on the application of data science in demand forecasting and inventory management and the prospect of the supply chain. New approaches including ARIMA, LSTM networks, hybrid models and Machine learning based forecasting techniques have shown better performances and flexibility over conventional approaches. Predictive analytics has been incorporated into the inventory management system to support dynamic replenishment approaches, precise demand forecasting, and lower costs of overstocking and stockouts. However, when introducing external variables like seasonality, macroeconomic variables, and disruptive events into the models, the predictive models become even more realistic as the real world is much more complex. However, there are still problems that remain: data quality, scalability, and the understanding of more complex models, which is why the development should continue.

For industry practitioners it means that transition to the data oriented approaches is beneficial and results in better efficiency, cost reduction, and increased customer satisfaction. First, the ability to use real-time analytics and adaptive forecasting allows organizations to stay on the right track while the new trends like federated learning and quantum computing open new opportunities. Academia, however, must pay attention to the ethical and technical issues surrounding such innovations, including ways of reducing bias in AI systems and enhancing the interpretability of those systems. It is suggested that, using behavioral economics, systems thinking, and, in particular, machine learning, one can gain more profound understanding of supply chain systems and their optimization.

VII. REFERENCES

[1] D. I. Purnamasari, V. A. Permadi, A. Saepudin, and R. P. Agusdin, “Demand Forecasting for Improved Inventory Management in Small and Medium-Sized Businesses,” *Jurnal Nasional Pendidikan Teknik Informatika (JANAPATI)*, vol. 12, no. 1, pp. 56–66, Mar. 2023, doi: https://doi.org/10.23887/janapati.v12i1.57144.

[2] Bokman, A., Fiedler, L., Perrey, J. and Pickersgill, A., “Five facts: How customer analytics boosts corporate performance. ,” *McKinsey & Company.*, 2014.

[3] X. Guo, C. Liu, W. Xu, H. Yuan, and M. Wang, “A Prediction-Based Inventory Optimization Using Data Mining Models,” *2014 Seventh International Joint Conference on Computational Sciences and Optimization*, Jul. 2014, doi: https://doi.org/10.1109/cso.2014.118.

[4] A. Aljohani, “Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility,” *Sustainability*, vol. 15, no. 20, p. 15088, 2023, doi: https://doi.org/10.3390/su152015088.

[5] P. Malik, Aditya Singh Dangi, A. Singh, Thakur Asst, and L. Mishra, “An Analysis of Time Series Analysis and Forecasting Techniques,” *IJARCCE*, vol. Vol-9, no. Issue-5, p. 2023, Nov. 2023, Available: https://www.researchgate.net/publication/375238697_An_Analysis_of_Time_Series_Analysis_and_Forecasting_Techniques

[6] P.-F. Pai and C.-S. Lin, “A hybrid ARIMA and support vector machines model in stock price forecasting,” *Omega*, vol. 33, no. 6, pp. 497–505, Dec. 2005.

[7] G. Peter. Zhang, “Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model,” *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003, doi: https://doi.org/10.1016/s0925-2312(01)00702-0.

[8] F. Badorf and K. Hoberg, “The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores,” *Journal of Retailing and Consumer Services*, vol. 52, no. 1, p. 101921, Jan. 2020, doi: https://doi.org/10.1016/j.jretconser.2019.101921.

[9] J. Wang, G. Q. Liu, and L. Liu, “A Selection of Advanced Technologies for Demand Forecasting in the Retail Industry,” *IEEE Xplore*, Mar. 01, 2019. https://ieeexplore.ieee.org/document/8713196

[10] F. Mohammad, D.-K. Kang, M. A. Ahmed, and Y.-C. Kim, “Energy Demand Load Forecasting for Electric Vehicle Charging Stations Network Based on ConvLSTM and BiConvLSTM Architectures,” *IEEE Access*, vol. 11, pp. 67350–67369, 2023, doi: https://doi.org/10.1109/ACCESS.2023.3274657.

[11] S. Punia, K. Nikolopoulos, S. P. Singh, J. K. Madaan, and K. Litsiou, “Deep learning with long short-term memory networks and random forests for demand forecasting in multi-channel retail,” *International Journal of Production Research*, vol. 58, no. 16, pp. 4964–4979, Mar. 2020, doi: https://doi.org/10.1080/00207543.2020.1735666.

[12] S. Shankar, S. Punia, and P. V. Ilavarasan, “Deep learning-based container throughput forecasting: a triple bottom line approach,” *Industrial Management & Data Systems*, vol. 121, no. 10, pp. 2100–2117, Jun. 2021, doi: https://doi.org/10.1108/imds-12-2020-0704.

[13] M. D. Geurts and J. Patrick Kelly, “Forecasting retail sales using alternative models,” *International Journal of Forecasting*, vol. 2, no. 3, pp. 261–272, Jan. 1986, doi: https://doi.org/10.1016/0169-2070(86)90046-4.

[14] K. J. Ferreira, B. H. A. Lee, and D. Simchi-Levi, “Analytics for an Online Retailer: Demand Forecasting and Price Optimization,” *Manufacturing & Service Operations Management*, vol. 18, no. 1, pp. 69–88, Feb. 2016, doi: https://doi.org/10.1287/msom.2015.0561.

[15] G. Jean, “Inventory Management Strategies: Balancing Cost, Efficiency, and Customer Satisfaction,” *Research Gate*, Nov. 25, 2024. https://www.researchgate.net/publication/386106872_Inventory_Management_Strategies_Balancing_Cost_Efficiency_and_Customer_Satisfaction

[16] D. A. Jerab and T. Mabrouk, “Achieving Competitive Advantage through Cost Leadership Strategy: Strategies for Sustainable Success,” *ResearchGate*, Sep. 18, 2023. https://www.researchgate.net/publication/374000449_Achieving_Competitive_Advantage_through_Cost_Leadership_Strategy_Strategies_for_Sustainable_Success

[17] L. B. Schwarz, “The Economic Order-Quantity (EOQ) Model,” *Building Intuition*, vol. 115, pp. 135–154, 2008, doi: https://doi.org/10.1007/978-0-387-73699-0_8.

[18] Y. W. Lok, S. S. Supadi, and K. B. Wong, “EOQ Models for Imperfect Items under Time Varying Demand Rate,” *Processes*, vol. 10, no. 6, p. 1220, Jun. 2022, doi: https://doi.org/10.3390/pr10061220.

[19] Shashwat Agrawal, Venkata Ramanaiah Chintha, Vishesh Narendra Pamadi, Anshika Aggarwal, and Prof.(Dr.) Punit Goel, “The Role of Predictive Analytics in Inventory Management,” *Universal Research Reports*, vol. 10, no. 4, pp. 456–472, Oct. 2023, doi: https://doi.org/10.36676/urr.v10.i4.1358.

[20] P. Suwignjo , L. Panjaitan , A. Baihaqy , and A. Rusdiansyah , “Predictive Analytics to Improve Inventory Performance: A Case Study of an FMCG Company,” *Operations and Supply Chain Management: An International Journal*, vol. 16, no. 2, pp. 293–310, Jun. 2023, doi: https://doi.org/10.31387/oscm0530390.

[21] B. N. Pawar and Jrtcse Journal, “The role of predictive analytics in supply chain optimization,” vol. 12, no. 1, pp. 16–26, May 2024, Available: https://www.researchgate.net/publication/383148496_The_role_of_predictive_analytics_in_supply_chain_optimization

[22] R. P. Tripathi, “Innovative Approach of EOQ Structure for Decaying Items with Time Sensitive Demand, Cash- Discount, Shortages and Permissible Delay in Payments,” *International Journal of Applied and Computational Mathematics*, vol. 7, no. 3, Apr. 2021, doi: https://doi.org/10.1007/s40819-021-01003-8.

[23] Olaoye, G., “Developing Predictive Models for Inventory Optimization (No. 13396). EasyChair.,” 2024.

[24] Kaul, D. and Khurana, R., “Ai-driven optimization models for e-commerce supply chain operations: Demand prediction, inventory management, and delivery time reduction with cost efficiency considerations.,” *International Journal of Social Analytics.*, vol. 7, no. 12, pp. 59–77, 2022.

[25] J. María and V. Barberán, “Adding external factors in Time Series Forecasting,” 2020. Available: https://www.diva-portal.org/smash/get/diva2:1520766/FULLTEXT01.pdf

[26] T. Tunç and A. Büyükkeklik, “Reducing the Negative Effects of Seasonal Demand Fluctuations: A Proposal Based On Cost-Benefit Analysis,” *International Journal of Engineering Research and Applications*, vol. 07, no. 03, pp. 38–46, Mar. 2017, doi: https://doi.org/10.9790/9622-0703033846.

[27] A. Borucka, “Seasonal Methods of Demand Forecasting in the Supply Chain as Support for the Company’s Sustainable Growth,” *Sustainability*, vol. 15, no. 9, pp. 7399–7399, Apr. 2023, doi: https://doi.org/10.3390/su15097399.

[28] Y. Danfeng and W. Jing, “Subway Passenger Flow Forecasting With Multi-Station and External Factors,” *IEEE Access*, vol. 7, pp. 57415–57423, 2019, doi: https://doi.org/10.1109/access.2019.2914239.

[29] F. Ohler, Karl-Heinz Krempels, and S. Möbus, “Forecasting Public Transportation Capacity Utilisation Considering External Factors,” pp. 300–311, Jan. 2017, doi: https://doi.org/10.5220/0006345703000311.

[30] J. M. Martin-Moreno, A. Alegre-Martinez, V. Martin-Gorgojo, J. L. Alfonso-Sanchez, F. Torres, and V. Pallares-Carratala, “Predictive Models for Forecasting Public Health Scenarios: Practical Experiences Applied during the First Wave of the COVID-19 Pandemic,” *International Journal of Environmental Research and Public Health*, vol. 19, no. 9, p. 5546, May 2022, doi: https://doi.org/10.3390/ijerph19095546.

[31] A. I. Bilal, U. S. Bititci, and T. G. Fenta, “Challenges and the Way Forward in Demand-Forecasting Practices within the Ethiopian Public Pharmaceutical Supply Chain,” *Pharmacy*, vol. 12, no. 3, p. 86, Jun. 2024, doi: https://doi.org/10.3390/pharmacy12030086.

[32] S. Kumar, “Data Silos -A Roadblock for AIOps,” Dec. 10, 2023. https://www.researchgate.net/publication/376392595_Data_Silos_-A_Roadblock_for_AIOps

[33] T. Saeed, “Data Mining for Small and Medium Enterprises: A Conceptual Model for Adaptation,” *Intelligent Information Management*, vol. 12, no. 05, pp. 183–197, 2020, doi: https://doi.org/10.4236/iim.2020.125011.

[34] S. Daniel, Seraphina Brightwood, and J. Oluwaseyi, “Cloud-based big data analytics (aws, azure, google cloud),” Oct. 15, 2024. https://www.researchgate.net/publication/385885475_Cloud-based_big_data_analytics_aws_azure_google_cloud

[35] T. H. Gomes Lobato, R. Sottek, and M. Vorlaender, “Implementing neural networks in low-latency audio applications,” *The Journal of the Acoustical Society of America*, vol. 153, no. 3_supplement, pp. A105–A105, Mar. 2023, doi: https://doi.org/10.1121/10.0018318.

[36] G. B. Mensah, “Artificial intelligence and ethics: A comprehensive review of bias mitigation, transparency, and accountability in AI systems,” *ResearchGate*, 2023, doi: https://doi.org/10.13140/RG.2.2.23381.19685/1.

[37] D. Patil, “Explainable Artificial Intelligence (XAI): Enhancing transparency and trust in machine learning models,” Nov. 06, 2024. https://www.researchgate.net/publication/385629166_Explainable_Artificial_Intelligence_XAI_Enhancing_transparency_and_trust_in_machine_learning_models

[38] S. Ali *et al.*, “Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence,” *Information*

Fusion, vol. 99, no. 101805, p. 101805, Apr. 2023, doi: https://doi.org/10.1016/j.inffus.2023.101805.