Optimizing Grocery Quality and Supply Chain Efficiency Using AI-Driven Predictive Logistics

AREEBA FAROOQ[1], ANATE BENOIT NICAISE ABBEY[2], EKENE CYNTHIA ONUKWULU[3]

[1]*Amazon Grocery Logistics, New York, USA*

[2]*Altice USA, Plano, TX, USA*

[3]*Independent Researcher, Nigeria*

Abstract- The grocery supply chain is a complex network that demands precision in managing product quality, minimizing waste, and ensuring efficient logistics. This paper explores the transformative potential of AI-driven predictive logistics in optimizing grocery supply chains, focusing on its ability to enhance forecasting accuracy, reduce waste, and ensure product freshness. It examines the role of predictive analytics in addressing supply chain challenges and highlights AI's contributions to improving quality monitoring and real-time tracking. The paper also identifies barriers to implementation, such as data availability, integration complexities, and cost, while presenting actionable strategies for stakeholders to overcome these challenges. By integrating advanced technologies and fostering collaboration, grocery supply chains can achieve unprecedented efficiency, sustainability, and customer satisfaction.

Indexed Terms- Predictive logistics, Grocery supply chain, Artificial intelligence, Product quality optimization, Real-time tracking, Supply chain efficiency

I. INTRODUCTION

Ensuring the quality of groceries and optimizing the efficiency of supply chains are critical challenges in today's fast-paced and highly competitive retail environment. Grocery supply chains, which encompass processes from production and distribution to retailing, face several hurdles (Mahroof, Omar, & Kucukaltan, 2022). These include variability in demand, perishability of products, and logistical inefficiencies that can lead to significant financial losses and consumer dissatisfaction (Denuwara, Maijala, & Hakovirta, 2021). Furthermore, the growing focus on sustainability and reducing food waste adds complexity to managing these supply chains (Neboh & Mbhele, 2020). Balancing these factors requires innovative solutions capable of addressing both operational challenges and broader societal concerns.

AI-driven predictive logistics has emerged as a transformative approach to overcoming these challenges. By leveraging advanced data analytics and machine learning, predictive logistics facilitates accurate demand forecasting, streamlined inventory management, and efficient routing of deliveries (Dev, Shankar, & Qaiser, 2020). This technology enables businesses to anticipate disruptions, optimize resources, and ensure that grocery products reach consumers in optimal condition (Shin, Van Thai, Grewal, & Kim, 2017). The integration of predictive tools is particularly crucial for perishables, where freshness and timely delivery are paramount. As a result, predictive logistics improves operational efficiency, enhances customer satisfaction, and reduces environmental impacts, aligning with global sustainability goals (Jeble et al., 2018).

The objectives of this paper are threefold: first, to explore the role of predictive analytics in addressing inefficiencies within grocery supply chains; second, to examine the specific applications of AI in ensuring product quality and reducing waste; and third, to identify challenges and opportunities associated with implementing these technologies. This paper aims to offer actionable insights for industry stakeholders, including producers, retailers, and policymakers, by providing a conceptual framework for understanding the integration of predictive logistics into grocery supply chains.

II. THE ROLE OF PREDICTIVE ANALYTICS IN SUPPLY CHAIN OPTIMIZATION

Predictive analytics is revolutionizing supply chain management by offering businesses the ability to anticipate trends, optimize operations, and respond proactively to challenges. This data-driven approach involves the use of statistical algorithms and machine learning techniques to analyze historical and real-time data (Aljohani, 2023). The goal is to forecast future outcomes, enabling informed decision-making across various aspects of the supply chain. Within the context of grocery supply chains, predictive analytics holds immense potential for addressing long-standing inefficiencies while enhancing operational efficiency and customer satisfaction.

2.1 Predictive Analytics and Its Applications in Logistics

At its core, predictive analytics involves harnessing data to predict future scenarios and outcomes. This capability is especially critical in logistics, where decision-making is often reactive due to the unpredictability of demand, transportation disruptions, and supplier variability (Hosseini et al., 2019). By integrating predictive tools, businesses can transition from reactive to proactive strategies, significantly reducing uncertainty.

In grocery supply chains, predictive analytics can be applied to demand forecasting, inventory management, and route optimization (Nimmagadda, 2021). Accurate demand forecasts, for instance, allow retailers to align their stock levels with consumer purchasing patterns, minimizing instances of overstocking or stockouts. This is particularly valuable for perishable goods as it helps reduce spoilage and ensures that fresh products are available to consumers (Kirci, Isaksson, & Seifert, 2022).

Another key application is in inventory management. Predictive models analyze data on shelf life, sales trends, and weather patterns to determine optimal stock levels. This capability reduces holding costs and prevents wastage, thereby improving profitability (Bradlow, Gangwar, Kopalle, & Voleti, 2017). Furthermore, in logistics and distribution, predictive tools enable the optimization of delivery routes and schedules. Businesses can identify the most efficient pathways by analyzing factors such as traffic patterns, fuel costs, and delivery deadlines, ensuring timely deliveries while minimizing costs (Tadayonrad & Ndiaye, 2023).

2.2 Impact on Forecasting Demand, Reducing Waste, and Improving Efficiency

Demand forecasting is one of the most critical aspects of supply chain optimization, and predictive analytics has proven to be a game-changer in this domain. Traditional forecasting methods often rely on historical sales data alone, which may not account for dynamic factors such as changing consumer preferences, market trends, and seasonal fluctuations (Verboeket & Krikke, 2019). Predictive models, however, incorporate a wide range of variables, including external data such as economic indicators and social trends, to provide more accurate and granular forecasts. This precision enables grocery retailers to plan their procurement and production processes more effectively, ensuring that supply matches demand (Blazquez & Domenech, 2018).

Predictive analytics also plays a significant role in reducing waste by improving the accuracy of demand forecasts. Overproduction or overordering due to inaccurate predictions leads to excessive inventory, much of which may go unsold or perish before it can be utilized (Avittathur & Ghosh, 2020). Conversely, underestimating demand can result in stockouts, forcing businesses to miss sales opportunities and disappoint customers. Predictive tools mitigate these risks by providing insights that allow for more balanced inventory management. For perishable items, this means fewer expired products and lower disposal costs, contributing to both economic and environmental benefits (Adedeji, 2020).

Efficiency gains are another major outcome of predictive analytics in grocery supply chains. Streamlined inventory management and optimized delivery schedules reduce operational costs and improve resource utilization (Nimmagadda, 2021). For example, predictive tools can identify trends in customer purchasing behavior, allowing businesses to preemptively allocate resources where they are most needed. This level of precision reduces unnecessary expenditures and improves overall supply chain resilience (Aljohani, 2023).

Additionally, predictive analytics enhances supplier collaboration by providing accurate forecasts that suppliers can use to align their production schedules. This alignment reduces lead times and ensures a steady flow of goods, minimizing disruptions and bottlenecks. For logistics providers, predictive tools can optimize fleet utilization by forecasting demand for transportation services, allowing for better allocation of vehicles and drivers (Seyedan & Mafakheri, 2020).

III. AI-DRIVEN APPROACHES FOR ENHANCING GROCERY QUALITY

Artificial intelligence (AI) has introduced groundbreaking changes in how grocery supply chains manage and ensure product quality (Nimmagadda, 2021). By leveraging data and machine learning algorithms, AI offers solutions to address critical challenges such as maintaining freshness, optimizing shelf life, and monitoring quality throughout the supply chain (Marr, 2019). These advancements are essential for meeting consumer expectations, minimizing waste, and fostering operational efficiency.

3.1 Techniques for Ensuring Product Freshness and Shelf-Life Optimization

Freshness is a key determinant of consumer satisfaction and brand loyalty in the grocery sector. Ensuring that perishable items reach customers in optimal condition requires precise and proactive management throughout the supply chain. AI-driven tools excel in addressing this challenge by utilizing data to monitor, predict, and enhance product freshness (Aleruchi, 2019).

One prominent technique involves the use of machine learning models to analyze historical and real-time data related to product life cycles. These models can predict the remaining shelf life of perishable goods by considering variables such as temperature, humidity, and transit times. By providing accurate predictions, AI enables supply chain managers to prioritize the distribution of items nearing their expiration dates, ensuring they reach consumers before they lose freshness (da Costa et al., 2022).

AI also facilitates dynamic inventory management by optimizing stock rotation. Algorithms can identify which products should be sold first based on their condition, reducing spoilage and ensuring that only the freshest items remain available for sale (Adedeji, 2020). Furthermore, AI tools can assist in designing smarter packaging solutions that extend shelf life. For instance, AI-powered simulations can predict the impact of different materials and packaging designs on product longevity, enabling manufacturers to make informed choices (Kaur et al., 2023).

Additionally, AI plays a critical role in demand planning. AI systems can anticipate demand fluctuations by analyzing consumer buying patterns, seasonal trends, and external factors like weather forecasts. This helps retailers stock the right quantities of perishable goods, minimizing instances of overstocking or understocking that could compromise freshness or lead to waste (Aderibigbe, Ani, Ohenhen, Ohalete, & Daraojimba, 2023).

3.2 Use of AI in Quality Monitoring and Real-Time Tracking

Monitoring product quality across the supply chain is complex, particularly for perishable groceries. AI enhances this process by automating quality assessments and providing real-time visibility into product conditions. These capabilities ensure that potential quality issues are identified and addressed before they affect consumers. One significant application of AI in quality monitoring is the use of computer vision technology (Pounds et al., 2022). Machine learning algorithms can analyze images or videos of products to detect defects, discoloration, or other quality issues. For instance, cameras installed in warehouses or production facilities can scan fruits and vegetables for bruises or blemishes, automatically removing subpar items from the supply chain. This automated inspection process is faster and more consistent than manual checks (Pettersson & Skäremo, 2023).

Real-time tracking systems powered by AI provide end-to-end visibility of product conditions during transit. These systems often integrate with Internet of Things (IoT) sensors that monitor variables such as temperature, humidity, and vibration. AI analyzes the data collected by these sensors to detect anomalies and predict potential risks to product quality. For example, suppose a temperature excursion occurs during transportation. In that case, AI can alert logistics teams to take corrective action, such as rerouting shipments or adjusting storage conditions (Rane, Choudhary, & Rane, 2023).

Moreover, AI-enabled blockchain technology is increasingly being used to enhance traceability and accountability within grocery supply chains. By recording every transaction and condition change in a tamper-proof digital ledger, AI ensures that stakeholders can trace the journey of each product from farm to shelf. This transparency builds consumer trust and aids in quality assurance and regulatory compliance (Ellahi, Wood, & Bekhit, 2023). AI also plays a role in enhancing supplier collaboration. Predictive analytics and real-time data sharing allow suppliers and retailers to align their quality standards more effectively. For example, AI can identify trends in supplier performance, enabling businesses to work closely with their partners to address recurring quality issues and improve overall supply chain reliability (Nimmagadda, 2023).

IV. CHALLENGES AND OPPORTUNITIES IN IMPLEMENTING PREDICTIVE LOGISTICS

The implementation of predictive logistics in grocery supply chains offers significant potential for enhancing efficiency, reducing waste, and improving customer satisfaction. However, it is not without challenges. Barriers such as data availability, integration complexities, and the financial burden of adopting new technologies often hinder widespread adoption. Conversely, these challenges pave the way for innovative solutions and new opportunities, particularly as the technology matures and businesses become more adept at leveraging its capabilities.

4.1 Barriers Such as Data Availability, Integration, and Cost

One of the most significant hurdles in implementing predictive logistics is the availability of high-quality data. Predictive models rely heavily on comprehensive, accurate, and up-to-date datasets to generate actionable insights. However, many grocery supply chains operate in environments where data collection is fragmented or inconsistent (Pegorin, 2023). For instance, smaller suppliers or regional distributors may lack the infrastructure to gather and share real-time data, creating gaps in the information flow. Furthermore, data silos within organizations prevent seamless sharing between departments, limiting the effectiveness of predictive tools (Islam, 2023).

Integration challenges also pose a considerable barrier. The implementation of predictive logistics requires harmonizing data from various sources, including sensors, enterprise resource planning (ERP) systems, and customer relationship management platforms. Many businesses, particularly those with legacy systems, find it difficult to integrate these disparate data streams into a unified platform. Incompatibility between existing systems and new technologies can result in delays, increased costs, and suboptimal performance of predictive tools (Birkel, Kopyto, & Lutz, 2020).

Cost is another critical concern, especially for small and medium-sized enterprises (SMEs). The deployment of predictive logistics involves significant upfront investments in technology, infrastructure, and training. These costs may deter businesses from adopting the technology, particularly if they are unsure of the return on investment. Additionally, ongoing expenses for software maintenance, data storage, and system upgrades can strain financial resources (Umair & Dilanchiev, 2022). Finally, the complexity of managing change within organizations cannot be underestimated. Transitioning to predictive logistics requires a cultural shift and buy-in from stakeholders at all levels. Employees may resist adopting new technologies due to a lack of understanding or fear of redundancy, further complicating the implementation process (Cichosz, Wallenburg, & Knemeyer, 2020).

4.2 Emerging Opportunities for Innovation and Scalability

Despite these challenges, the rapid evolution of technology and growing demand for efficiency are creating numerous opportunities for innovation and scalability in predictive logistics. One of the most promising developments is the increasing availability of affordable and scalable cloud computing solutions. These platforms allow businesses to store and process large volumes of data without the need for expensive on-premises infrastructure, lowering the entry barrier for adopting predictive tools.

Artificial intelligence and machine learning are enhancing the accuracy and functionality of predictive models. These improvements enable businesses to analyze complex data patterns more effectively, resulting in better forecasts and more informed decision-making (Bharadiya, 2023). For example, predictive tools can now incorporate external variables such as weather forecasts, traffic conditions, and economic indicators, allowing for even more precise logistics planning.

Collaboration between stakeholders within the supply chain is another area ripe for innovation. Shared data ecosystems, facilitated by blockchain technology, can help overcome data availability issues by ensuring that all parties have access to the same, tamper-proof information. This transparency fosters trust and accountability while improving the overall efficiency of the supply chain.

Opportunities also exist in the form of government incentives and industry partnerships aimed at encouraging the adoption of advanced logistics technologies. Many governments and trade organizations are recognizing the economic and environmental benefits of reducing waste and improving supply chain efficiency. As a result, they are providing grants, tax incentives, and technical support to businesses investing in predictive logistics (Xie, Zhao, Chen, & Allen, 2022).

Moreover, the growing consumer demand for sustainability and traceability presents a unique opportunity for businesses to differentiate themselves. By leveraging predictive tools, grocery supply chains can reduce waste, lower carbon emissions, and provide consumers with detailed information about the journey of their products. This meets regulatory and market demands and enhances brand reputation and customer loyalty (Zhang, Wedel, & Bloem, 2022). As predictive logistics becomes more mainstream, economies of scale are likely to drive down costs, making the technology more accessible to smaller players. Additionally, advancements in no-code and low-code platforms are simplifying the implementation process, enabling businesses to deploy predictive solutions without requiring extensive technical expertise.

V. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Predictive logistics is reshaping grocery supply chains by providing accurate forecasts, optimizing resource allocation, and ensuring product quality. These tools mitigate the risks associated with overstocking, stockouts, and wastage through advanced algorithms and data-driven insights, particularly for perishable items. They also enable businesses to adapt swiftly to disruptions caused by market fluctuations, transportation delays, or unforeseen events.

For stakeholders, the implications are far-reaching. Producers can benefit from more accurate demand projections, enabling them to align production schedules with retailer requirements. This reduces waste and enhances profitability. Distributors and logistics providers gain from route optimization and real-time tracking, which lower transportation costs and improve delivery reliability. Retailers, in turn, can maintain consistent inventory levels, ensuring that fresh products are always available to consumers.

Consumers also stand to gain significantly from the adoption of predictive logistics. Enhanced supply chain efficiency translates to better product availability, improved freshness, and reduced costs, creating a more satisfying shopping experience. Additionally, the sustainability benefits, such as minimized waste and lower carbon footprints, align with growing consumer demand for environmentally conscious practices. Despite its advantages, the implementation of predictive logistics is not without challenges. Issues such as data accessibility, integration difficulties, and the financial burden of adopting new technologies must be addressed to unlock its full potential. Collaboration among stakeholders and investment in infrastructure and training will be critical to overcoming these barriers.

5.2 Recommendations

To fully harness the capabilities of predictive logistics, businesses must adopt a strategic and phased approach that considers technological, organizational, and collaborative factors. This transformation's core is the availability of high-quality, real-time data. Investments in sensors, IoT devices, and cloud-based platforms are crucial to enabling seamless data collection, storage, and analysis. Ensuring data accuracy and consistency across supply chain operations is equally critical, as reliable predictive models depend on robust data inputs. With accurate data infrastructure in place, businesses can lay a strong foundation for implementing predictive logistics effectively.

A collaborative approach is essential to overcome challenges such as data silos and lack of transparency within the supply chain. Producers, distributors, and retailers must work together to create shared data ecosystems that facilitate real-time information exchange. Blockchain technology can play a pivotal role in maintaining data integrity and traceability, ensuring all stakeholders can access tamper-proof, consistent information. This collaboration fosters trust and optimizes decision-making across the supply chain, enabling participants to respond quickly to dynamic market conditions and consumer demands.

Scalability and cost-efficiency are key considerations for businesses adopting predictive logistics, especially for smaller players. Leveraging cloud-based analytics platforms and machine learning algorithms allows businesses to process large volumes of data without significant infrastructure investments. Open-source software and no-code platforms further lower barriers to entry, enabling organizations with limited technical expertise to access advanced predictive tools. These scalable solutions democratize the benefits of predictive logistics, making them accessible to businesses of all sizes.

The successful implementation of predictive logistics also requires a cultural shift within organizations, driven by effective training and change management. Employees must be equipped with the skills to use predictive tools effectively, which calls for comprehensive training programs tailored to their roles. Clear communication about the benefits of predictive logistics, such as improved efficiency and decision-making, can help mitigate resistance to change. By fostering a sense of ownership among staff and aligning their efforts with organizational goals, businesses can create a supportive environment for technological adoption.

Finally, continuous monitoring and alignment with sustainability goals are critical for long-term success. Businesses should establish key performance indicators to track the effectiveness of predictive tools and adapt them to evolving market conditions through regular feedback loops. Additionally, predictive logistics can significantly contribute to sustainability by reducing waste and emissions, aligning with both regulatory standards and consumer expectations. Government incentives and industry partnerships further support these efforts, providing financial and technical assistance to encourage broader adoption. By integrating predictive logistics into sustainability strategies, businesses can enhance their operational efficiency while building consumer trust and loyalty.

REFERENCES

[1] Adedeji, A. E. (2020). Fresh Food Products Inventory Control Management: the challenges in avoiding perishability at the retailers' shelf. In.

[2] Aderibigbe, A. O., Ani, E. C., Ohenhen, P. E., Ohalete, N. C., & Daraojimba, D. O. (2023). Enhancing energy efficiency with ai: a review of machine learning models in electricity demand forecasting. *Engineering Science & Technology Journal, 4*(6), 341-356.

[3] Aleruchi, T. C. (2019). *Strategies to Minimize Perishable Food Loss in the Retail Grocery Business.* Walden University,

[4] Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. *Sustainability, 15*(20), 15088.

[5] Avittathur, B., & Ghosh, D. (2020). *Excellence in supply chain management*: Routledge.

[6] Bharadiya, J. P. (2023). Machine learning and AI in business intelligence: Trends and opportunities. *International Journal of Computer (IJC), 48*(1), 123-134.

[7] Birkel, H., Kopyto, M., & Lutz, C. (2020). *Challenges of applying predictive analytics in transport logistics.* Paper presented at the

Proceedings of the 2020 on Computers and People Research Conference.

[8] Blazquez, D., & Domenech, J. (2018). Big Data sources and methods for social and economic analyses. *Technological Forecasting and Social Change, 130*, 99-113.

[9] Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The role of big data and predictive analytics in retailing. *Journal of retailing, 93*(1), 79-95.

[10] Cichosz, M., Wallenburg, C. M., & Knemeyer, A. M. (2020). Digital transformation at logistics service providers: barriers, success factors and leading practices. *The International Journal of Logistics Management, 31*(2), 209-238.

[11] da Costa, T. P., Gillespie, J., Cama-Moncunill, X., Ward, S., Condell, J., Ramanathan, R., & Murphy, F. (2022). A systematic review of real-time monitoring technologies and its potential application to reduce food loss and waste: Key elements of food supply chains and IoT technologies. *Sustainability, 15*(1), 614.

[12] Denuwara, N., Maijala, J., & Hakovirta, M. (2021). The impact of unmanned stores' business models on sustainability. *SN business & economics, 1*(10), 143.

[13] Dev, N. K., Shankar, R., & Qaiser, F. H. (2020). Industry 4.0 and circular economy: Operational excellence for sustainable reverse supply chain performance. *Resources, Conservation and Recycling, 153*, 104583.

[14] Ellahi, R. M., Wood, L. C., & Bekhit, A. E.-D. A. (2023). Blockchain-based frameworks for food traceability: a systematic review. *Foods, 12*(16), 3026.

[15] Hosseini, S., Tajik, N., Ivanov, D., Sarder, M., Barker, K., & Al Khaled, A. (2019). Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics, 213*, 124-137.

[16] Islam, J. (2023). Leveraging Advanced Analytics for Backorder Prediction and Optimization of Business Operations in the Supply Chain.

[17] Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management, 29*(2), 513-538.

[18] Kaur, K., Priyanka, Kaur, G., Singh, B., Sehgal, S., & Trehan, S. (2023). Artificial Intelligence (AI) as a Transitional Tool for Sustainable Food Systems. In *Sustainable Food Systems (Volume II) SFS: Novel Sustainable Green Technologies, Circular Strategies, Food Safety & Diversity* (pp. 305-328): Springer.

[19] Kirci, M., Isaksson, O., & Seifert, R. (2022). Managing perishability in the fruit and vegetable supply chains. *Sustainability, 14*(9), 5378.

[20] Mahroof, K., Omar, A., & Kucukaltan, B. (2022). Sustainable food supply chains: overcoming key challenges through digital technologies. *International Journal of Productivity and Performance Management, 71*(3), 981-1003.

[21] Marr, B. (2019). *Artificial intelligence in practice: how 50 successful companies used AI and machine learning to solve problems*: John Wiley & Sons.

[22] Neboh, N., & Mbhele, T. (2020). Supply chain resilience and design in retail supermarkets. *Journal of Contemporary Management, 17*(2), 51-73.

[23] Nimmagadda, V. S. P. (2021). Artificial Intelligence for Real-Time Logistics and Transportation Optimization in Retail Supply Chains: Techniques, Models, and Applications. *Journal of Machine Learning for Healthcare Decision Support, 1*(1), 88-126.

[24] Nimmagadda, V. S. P. (2023). Artificial Intelligence for Supply Chain Visibility and Transparency in Retail: Advanced Techniques, Models, and Real-World Case Studies. *Journal of Machine Learning in Pharmaceutical Research, 3*(1), 87-120.

[25] Pegorin, E. F. (2023). Data-driven Insights for Grocery Retailers: Developing a Serverless Tool for Business Analysis.

[26] Pettersson, I., & Skäremo, J. (2023). Quality Control: Detect Visual Defects on Products Using Image Processing and Deep Learning. In.

[27] Pounds, K., Bao, H., Luo, Y., De, J., Schneider, K., Correll, M., & Tong, Z. (2022). Real-time and rapid food quality monitoring using smart sensory films with image analysis and machine learning. *ACS Food Science & Technology, 2*(7), 1123-1134.

[28] Rane, N., Choudhary, S., & Rane, J. (2023). Artificial Intelligence (AI) and Internet of Things (IoT)-based sensors for monitoring and controlling in architecture, engineering, and construction: applications, challenges, and opportunities. *Available at SSRN 4642197*.

[29] Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. *Journal of Big Data, 7*(1), 53.

[30] Shin, Y., Van Thai, V., Grewal, D., & Kim, Y. (2017). Do corporate sustainable management activities improve customer satisfaction, word of mouth intention and repurchase intention? Empirical evidence from the shipping industry. *The International Journal of Logistics Management, 28*(2), 555-570.

[31] Tadayonrad, Y., & Ndiaye, A. B. (2023). A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply Chain Analytics, 3*, 100026.

[32] Umair, M., & Dilanchiev, A. (2022). Economic recovery by developing business starategies: mediating role of financing and organizational culture in small and medium businesses. *Proceedings book, 683*.

[33] Verboeket, V., & Krikke, H. (2019). Additive manufacturing: A game changer in supply chain design. *Logistics, 3*(2), 13.

[34] Xie, Y., Zhao, Y., Chen, Y., & Allen, C. (2022). Green construction supply chain management: Integrating governmental intervention and public–private partnerships through ecological modernisation. *Journal of cleaner production, 331*, 129986.

[35] Zhang, J., Wedel, M., & Bloem, M. W. (2022). Mitigating food waste in the retail supply chain: Marketing solutions. *Journal of Sustainable Marketing, 3*(2), 87-97.