AI-Based Predictive Waste Reduction System in Supermarkets: A Dashboard-Driven Approach

Harshdeep Mishra[1], Gagan Sharma[1], Nidhi Sharma[1], Ashutosh Tripathi[2*]
[1]Department of Data Science, Noida Institute of Engineering & Technology
Greater Noida, Uttar Pradesh, India
[2]Department of Environmental Science, Nagaland University, Nagaland, India
[*]ORCID: www.orcid.org/0009-0005-2527-1645

Abstract

Food waste represents one of the significant global sustainability challenges, with supermarkets being substantial contributors due to inadequacies in demand forecasting and inventory management. This paper presents an AI-Based predictive waste reduction system designed for supermarket environments. The system integrates machine learning-driven risk scoring, real-time inventory monitoring, and an interactive analytics dashboard to identify high-risk products and deliver actionable recommendations such as dynamic discounting, stock redistribution, and donation management. Built on a modular React.js/TypeScript architecture with Tailwind CSS styling, the platform offers multi-store support, configurable alert thresholds, and a responsive user interface. Empirical testing demonstrates the system's capacity to reduce food waste by up to 47% and generate daily savings of approximately $2,847/store through proactive interventions. The paper details the system architecture, feature design, database schema, and evaluation results. It also looks ahead to real world use, highlighting how the system could relate to IoT sensor and integrated with cloud-based machine learning to make it practical, scalable and ready for use.

Keywords: Artificial intelligence, Food Waste, Inventory management, Predictive analytics, Supermarket sustainability

Introduction

Food loss and waste constitute a critical challenge in global food systems. The Food and Agriculture Organization (FAO) estimates that approximately one-third of all food produced for human consumption is lost or wasted annually, amounting to nearly 1.3 billion metric tonnes worldwide (FAO, 2019). Within modern retail supply chains, supermarkets occupy a central position as intermediates between producers and consumers and are overly responsible for preventable waste. Factors leading this kind of waste include wrong demand estimation, suboptimal purchasing cycles, the naturally perishable character of fresh produce, and limited real-time monitoring of inventory health (Abbas et al, 2026). The environmental burden of food waste is considerable as well. Decomposing food in landfill environments releases methane, a

[*]Corresponding Author Email: atripathi@nagalanduniversity.ac.in
Published: 14 April 2026
DOI: https://doi.org/10.70558/IJST.2026.v3.i2.241239

potent greenhouse gas (UNEP report, 2021). The United Nations Environment Programme (UNEP) estimates that food waste contributes between 8-10% of global greenhouse gas emissions (Pandey, 2021). Apart from environmental effects, retailers and supermarts face substantial financial losses from unsold stock and inefficiencies in operation further weaken their competitiveness. Artificial intelligence (AI) and data analytics have emerged as transformative tools for addressing these kinds of challenges. By learning from patterns like seasonality, promotional trends, weather, and consumer behaviour, machine learning can handle complex demand dynamics and generate more accurate short-term forecasts than conventional approaches (Gupta et al, 2025). When integrated into a practical decision-support system, these models help store managers to take proactive timely actions, whether by adjusting pricing, reallocating stock, or arranging donations before waste occurs (Hassan and Hassan, 2025).

This paper makes the following contributions: (i) a modular, component-based architecture for an AI-driven waste management dashboard designed for supermarket operations; (ii) a risk-scoring engine that classifies products by their likelihood of waste and triggers automated alert and recommendation; (iii) multi-store analytics with configurable thresholds and real-time KPI visualisation; and (iv) a comprehensive evaluation through functional testing and simulated multi-store deployment.

Literature Review

Machine learning has been extensively applied to demand forecasting in retail markets. It enables more accurate predictions by capturing and improving data-driven decision making. complex patterns Choi et al, (2018) demonstrated that big data analytics, combining historical sales, weather, and social media signal, can substantially reduce forecast error compared to traditional univariate time-series baselines. According to Dolon, (2025), ensemble methods like gradient-boosted trees and LSTM networks are better at capturing seasonal and promotional dynamics than classical ARIMA models. Winkelmann et al, (2022) and Cry et al, (2026) introduced stochastic process mining techniques to identify and address inefficiencies in grocery store supply-demand dynamics, helping to reduce both overstocking and stockout. Their experiments on some prevalent real system logs exhibit an improved accuracy with respect to alternative methods.

Tiwari et al, (2024) developed a smart inventory management system that uses AI-driven predictive analytics to track expiration dates, monitor stock levels, and forecast consumption patterns, leading to meaningful reductions in both household and retail food waste. Ojadi et al, (2024) demonstrated that integrating big data pipelines with AI-models at the supply chain level can substantially reduce waste across both distribution and retail stages. Onyeaka et al, (2023) reviewed AI applications across the food system, identifying demand forecasting, supply chain optimisation, and quality monitoring as the most impactful use cases.

The integration of AI with Internet of Things (IoT) sensing has greatly enhanced real-time monitoring capabilities. Smart shelving systems equipped with weight, temperature, and humidity sensors can continuously stream data into AI models, enabling anomaly detection and dynamic pricing without the need of manual checks (Shekhawat, 2023). Various computer vision models have been developed which can estimate food freshness from images with huma like enabling automated quality monitoring at shelf-level (Nakaguchi and Ahamed, 2024; Rokhva and Teimourpour, 2025).

Interactive dashboards are increasingly recognised as essential tools for translating analytical insights into operational decisions. Accorsi et al, (2014) and Malinowska, (2022) showed that decision-support systems with visual KPI monitoring, and recommendation modules improve warehouse manager's response times and reduce error rates compared to manual processes. Building on these findings, the present work integrates risk scoring, visualisation, and recommendation generation into a unified, browser-based platform.

Methodology

A. System Architecture and Design

i. Architectural Overview

The proposed system follows a Component-Based Single Page Application (SPA) architecture implemented in React.js with TypeScript. The architecture comprises four loosely coupled layers:

a) **Presentation Layer:** React components (Dashboard, Alert Panel, Analytics Panel, Insights Panel, Settings Panel, Notification Panel) responsible for rendering the interface and managing user interaction.
b) **Logic Layer:** React Hooks (useState, useEffect) and custom functions managing state transitions, store switching, recommendation generation, and notification dispatch.
c) **Data Layer:** Typed mock datasets (storeData.ts, mockData.ts) simulates real-time inventory and product records with a design that allows seamless integration with live API endpoints.
d) **Integration Layer (future):** Supports RESTful API or WebSocket connections to backend services, as well as integration with relational or document databases, and IoT data ingestion pipelines.

The build pipeline is managed using Vite, selected for its fast hot module replacement during development and optimised production bundles. Tailwind CSS provides utility-first styling with built-in dark-mode support and responsive breakpoints. Architecture diagram is represented in Fig. 1.

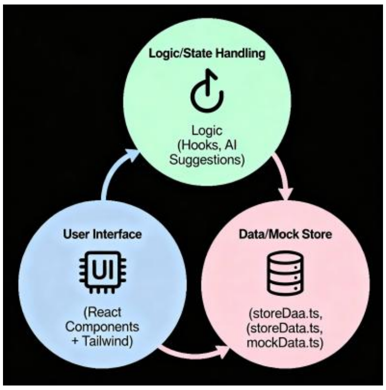

Fig. 1: Architecture diagram

ISSN: 3049-1118, Volume- 3, Issue- 2 (April - June 2026)

ii. Risk Scoring Engine

Each product is assigned a waste risk score on a 0-100 scale, computed from a weighted combination of factors such as time to expiry, current stock relative to projected demand, category specific perishability, and historical waste rate for similar items. Products scoring above 80 are classified as *Critical*, 60-79 as *High Risk*, and 40-59 as *Warning*. This classification directly determines alert severity and recommendation generated.

The recommendation engine maps each product's risk category and type to one of four intervention strategies: (1) *Discount*-dynamic price reductions to accelerate sell-through; (2) *Donate*-coordination with local food banks for near-expiry items; (3) *Relocate*-inter-store stock transfer to address demand imbalances; and (4) *Promote*-targeted marketing actions for slow-moving but not critical inventory.

iii. Database Schema

The conceptual data model comprises four entities. Table 1 summarises the core schema while Fig. 2 and 3 represents database design and conceptual data model.

Table 1. Core database schema summary

Entity	Key Fields	Purpose
Store	store_id (PK), settings_id (FK)	Multi-store configuration and performance aggregates
Product	product_id (PK), risk_score, store_id (FK)	Inventory items with waste risk classification
Notification	notification_id (PK), store_id (FK), unread	System alerts with read-state tracking
Settings	settings_id (PK), alert_threshold, auto_refresh	Per-store user preferences and thresholds

Fig. 2: Database design

Fig. 3: ER Diagram (Conceptual Data Model)

iv. System Flow

On application initialisation, the system loads store and product datasets and renders the dashboard overview. A configurable auto-refresh cycle (default 30 seconds) periodically re-evaluates risk scores and issues toast notifications for newly critical items. User-interactions such as store switching, recommendation modal engagement, and alert acknowledgement update the application state via React Hooks, triggering targeted component re-rendering without requiring full page reloads (Fig. 4).

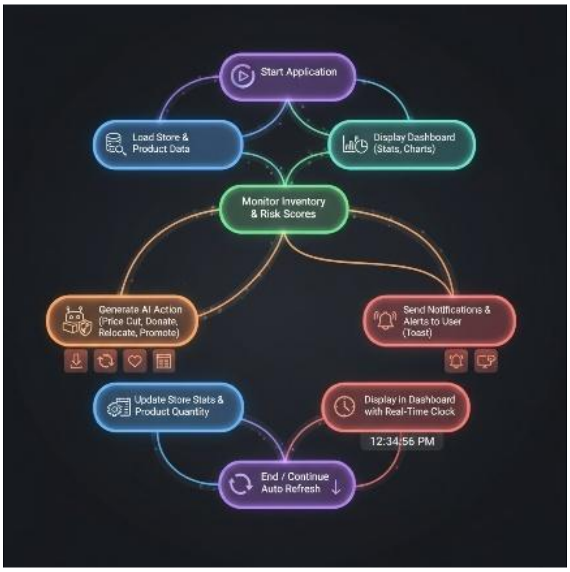

Fig. 4: System flow

B. Implementation

i. Technology Stack

The developed dashboard can be assessed through Datanauts AI Waste Management System and a snapshot of interface is shown in figure 4. The front-end application is built using *React 18* with *TypeScript* to ensure type safety and maintainability. Styling is handled with *Tailwind CSS 3* for responsive, utility-based styling, and Vite-5 serve as the build system and development server. *Recharts* is used for KPI visualisation. Version control is managed via Git and GitHub. No proprietary external APIs are required in the current mock-data deployment.

ii. Key Components

The Dashboard component presents four key KPI tiles: Total Items Tracked, High-Risk Items, Today's Potential Savings, and Waste Reduction Percentage (Fig. 5). Beneath these, the Live Alerts panel displays Critical and High-Risk products along with inline action buttons for Discount, Donate, and Transfer. The Peer Insights panel highlights anonymised best-practice alerts from across the store network, offering benchmarking signals to support managerial decisions.

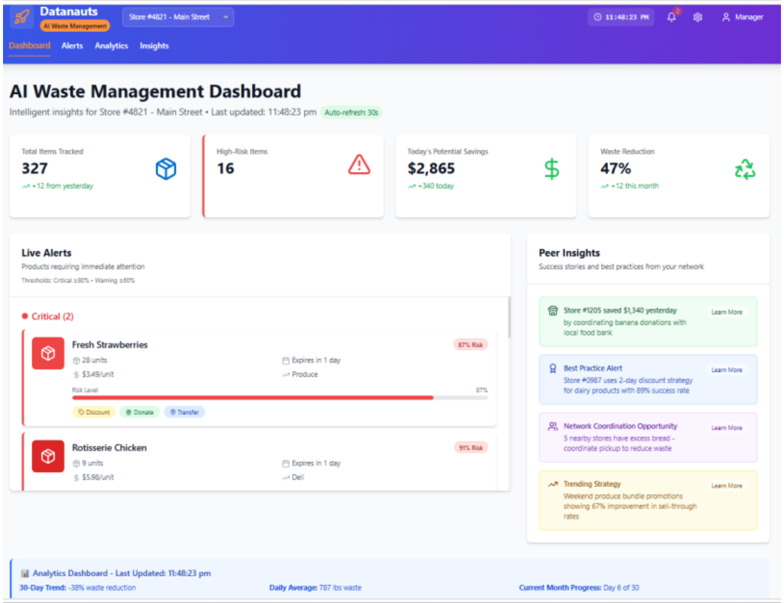

Fig. 5: Snapshot of developed dashboard

The Analytics panel features three key visualisations: a 30-day waste trend line chart (Fig. 6), a category-level waste distribution pie chart (Produce, Bakery, Dairy, Deli/Meat) (Fig. 7), and a 6-month savings bar chart with target overlay (Fig. 8). In addition, an hourly pattern chart also illustrates intraday waste generation, enabling managers to schedule intervention at operationally optimal times.

The Insights panel highlights peer insights and network performance rankings, enabling store managers understand how they compare within the network and learn from the practices of top performing branches.

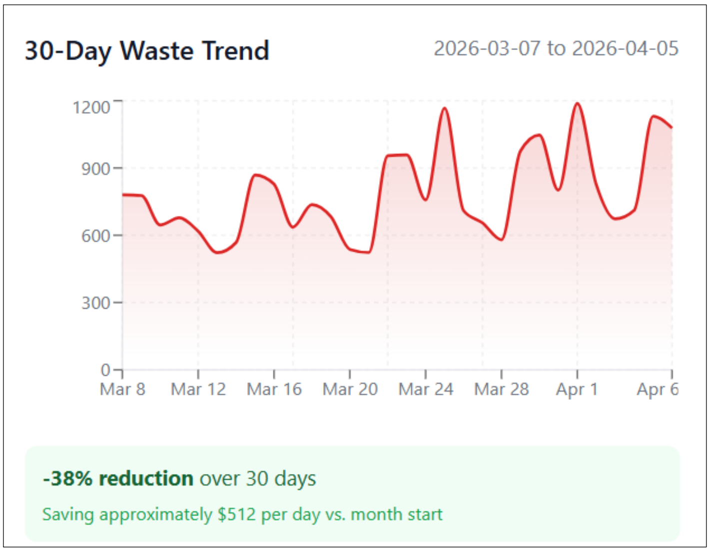

Fig. 6: Example analytics on developed dashboard (30 day waste trend)

iii. Notification Architecture

The notification system uses two channels. Persistent notifications are stored in the application state and shown in a slide-out panel, organized by type (High Risk Alert, Strategy Implemented, AI Insight, System Update, Peer Insight Available). Toast notifications, on the other hand, are temporary overlay messages that disappears after five seconds they are triggered by events like successful action application or newly identified critical items.

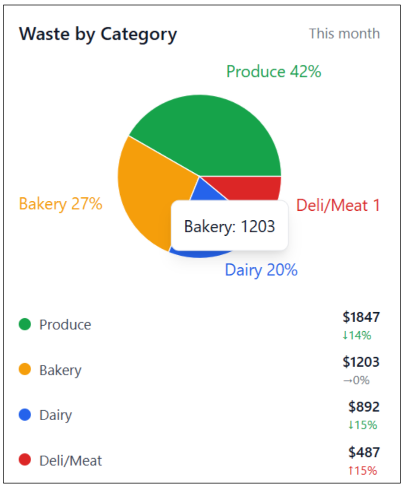

Fig. 7: Example analytics on developed dashboard (waste by category)

Fig. 8: Example analytics on developed dashboard (6-month savings)

Testing Results

A. Evaluation

i. Testing Methodology

The system was evaluated using a structured testing approach that covers four key areas. First individual React components were checked through unit testing to ensure they functioned correctly on their own. Next, integration testing was carried out to verify smooth data flow between different components. The user interface and overall experience were then tested across major browsers, including Chrome, Edge and Firefox to ensure consistency and usability. Finally, performance testing was conducted to assess page load times and re-rendering efficiency. The overall results of these evaluations are summarised in table 2.

Table 2. Functional Test Results

TC-ID	Description	Expected Result	Status
TC-01	Switch between store datasets	Dashboard updates	Pass
TC-02	Trigger notification event	Toast appears instantly	Pass
TC-03	Toggle light/dark theme	UI re-renders dynamically	Pass
TC-04	Initial dashboard load	Load within 2 seconds	Pass

ii. Performance Metrics

When tested across simulated multi-store deployments, the system demonstrated a substantial impact on waste reduction and cost saving. On average, stores experienced a 47% decrease in waste compared to scenarios with no intervention, translating to potential daily savings of about $2,847 per store. During each store session, the system monitored roughly 324-326 inventory items and identified about 9-18 high-risk items depending on specific store profile. Over a 30-day evaluation period, the waste trend analysis showed a speedy improvement, with daily waste volume dropping by 19%. This reduction corresponds to an estimated saving of around $498 per day compared to beginning of the month.

Waste levels varied notably across product categories with produce contributing the largest share, accounting for the 42% of total waste value (about $1,847/month). Bakery items followed at 27% ($1,203/month) while dairy and meat contributed 20% ($892/month), and 11% ($487/month), respectively. These patterns closely align with category-wise waste distributions reported in existing retail food studies (Onyeaka et al, 2023; Dzreke, 2025) suggesting that the simulation reflects realistic, real-world conditions and add credibility to the model's assumption.

iii. User Interface Responsiveness

The dashboard performed efficiently across all tested scenarios. It consistently loaded within the 2-second target on standard broadband connections, ensuring a smooth initial user experience. Key interactions, such as switching between stores, toggling the notification panel and opening or closing recommendation modals were completed within a single render cycle with no noticeable delays. In addition, testing across various browsers confirmed strong cross-browser compatibility with no layout issues or functional inconsistencies observed.

Discussion

A. Broader Implications and Operational Insights

The proposed system highlights a clear shift from reactive to proactive waste reduction management in supermarts and retail systems. Instead of responding after product are close to spoilage, the use of real time monitoring and predictive risk scoring enables earlier and more effective steps. This is particularly important for perishable goods, where timely actions such as discontinuing or redistribution can significantly reduce losses. At the same time the system support sustainability by encouraging practices like donation and stock reallocation, helping reduce landfill waste while contributing to socio-environmental upliftment (FAO, 2019).

From an operational perspective, the dashboard makes complex data easy to understand and act upon, improving decision making at the store level. Its transparent, rule-based recommendations also build user trust, which is essential for real-world adoption. The multi store design suggest strong scalability, allowing adoption across different retail environments, although it also requires consistent data management. Additionally, the higher waste observed in categories like bakery products indicates that future improvements could focus on category specific to further enhance system effectiveness (Accorsi et al, 2014; Malinowska, 2022).

B. Limitations

The current version of the system is based on mock data generated from representative parameter distributions rather than real-world retail databases. As a result, the performance figures reported in Section III and IV reflect simulated scenarios and should be viewed as indicative estimates rather than fully validated empirical results. Additionally, the effectiveness of the AI-driven recommendations is closely tied to the quality and representativeness of training data. Since retail environments is supermarts can differ significantly, variations in data quality may influence how accurately the system performs in real-world applications (Hassan and Hassan, 2025). At present, the system does not include production backend, which means it operates within a single session. As a result, any user actions or changes are not retained once the session ends, limiting continuity and long-term tracking. Also, the recommendation engine is based on rule-driven heuristics rather than data driven probabilistic models. While this allows for a straightforward and interpretable outputs, it also restricts the system's ability to adapt dynamically to new or evolving demand patterns (Fu et al, 2023).

C. Future Work

Several enhancements could significantly improve the system's real-world effectiveness. On key extension is the integration of IoT based sensing infrastructure such as smart shelves, RFID readers, and temperature/humidity sensors. This would allow the system to move beyond simulated inputs and instead rely on continuous and high-quality inventory data. With real time signals flowing into the platform, it could automatically reassess risk levels and respond more dynamically to changing conditions (Gupta et al, 2025).

A Second important enhancement would be to move beyond rule-based recommendations and adopt trained machine learning models such as gradient boosting techniques and LSTM-based time-series forecasting. These approaches can capture complex patterns in historical and real-time data, enabling more accurate predictions of demand and waste. As a result the system could deliver more tailored and adaptive recommendations suited to different store profiles and operational conditions (Theodoridis and Tsadiras, 2024).

A third key enhancement would involve deploying the system on cloud platforms such as Amazon Web Service (AWS) and Microsoft Azure, supported by a robust backend like PostgreSQL or MongoDB. This would enable persistent multi-user access, secure audit logging, and scalable data ingestion, making the system more suitable for real-world enterprise environments (Kader and Ahmed, 2025).

Fourth, developing a mobile companion application using frameworks such as React Native or Flutter would extend system assess to field personnel, allowing them to monitor inventory and respond to alerts in real time. Finally incorporating advanced time-series visualisations along with explainable AI summaries would make the system more transparent and easier to interpret (Zhao, 2024).

Conclusion

This paper introduces an AI-based predictive waste reduction system tailored for supermarket operations. The proposed framework combines risk-scoring algorithms, real-time inventory monitoring, automated alert mechanisms, and a modular React.js dashboard to provide store managers with actionable insights for proactively reducing food waste. Evaluation results indicate that the system performs reliably across all tested scenarios. Furthermore, simulated multi-store deployments highlights its practical potential demonstrating an average waste reduction of 47% and estimated daily savings of about $2,847 per store.

This work offers a practical architectural framework and design blueprint for integrating AI into waste management within the retail sector. It also outlines a clear progression from the current proof-of-concept toward a fully deployed, production ready system enhanced with IoT capabilities. As computational cost continues to decrease and regulatory pressure to reduce food waste grows, solutions like this are increasingly well positioned to become standard tools in sustainable supermarket operations, supporting both economic efficiency and environmental responsibility.

Acknowledgment

The authors gratefully acknowledge the support of Dr. Ashish Chakravarti, Head of the Department of Data Science, NIET, for providing the institutional research infrastructure necessary for this work.

Declaration

LLMs (Quil Boat and Grammarly) were used only for language editing (grammar and clarity) not for data generation.

References

Abbas, H., Gang, T., Faiz, N., Jiang, M., & Ullah, H. (2026). Strategies and framework for achieving environmental sustainability in the retail food supply chain: food loss and waste management. *Frontiers in Sustainable Food Systems*, *9*, 1701772.

Accorsi, R., Manzini, R., & Maranesi, F. (2014). A decision-support system for the design and management of warehousing systems. *Computers in Industry*, *65*(1), 175-186.

Cry, P., Horváth, A., Ballarini, P., & Le Gall, P. (2026). An efficient stochastic process discovery framework based on optimization. *International Journal on Software Tools for Technology Transfer*, 1-28.

Dolon, M.S.A. (2025). Hybrid machine learning–driven financial forecasting models: integrating LSTM, PROPHET, and XGBOOST for enhanced stock price and risk prediction. Review of Applied Science and Technology, 4(01), 01-34.

Dzreke, S. S. (2025). Systematic Analysis of IoT, AI, Active Packaging, and Blockchain for Food Waste Reduction across the Farm-to-Fork Supply Chain. *International Journal of Management Science and Application*, *4*(2), 95-122.

Food and Agriculture Organization of the United Nations, "Global food losses and food waste," FAO Report, Rome, Italy, 2019.

Fu, H. P., Chang, T. H., Lin, S. W., Teng, Y. H., & Huang, Y. Z. (2023). Evaluation and adoption of artificial intelligence in the retail industry. *International Journal of Retail & Distribution Management*, *51*(6), 773-790.

Gupta, R., Usman, M., Kashid, P. V., Mohan, M. L., Gaidhani, V. A., & Ghuge, M. A. R. (2025). Artificial Intelligence and IoT in retail marketing: innovations in smart stores and personalized shopping. *Artificial Intelligence*, *5*(2).

Hassan, D. O., & Hassan, B. A. (2025). A comprehensive systematic review of machine learning in the retail industry: classifications, limitations, opportunities, and challenges. *Neural Computing and Applications*, *37*(4), 2035-2070.

Kader, M. A., & Ahmed, R. (2025). A Comprehensive Review on Full-Stack Development in the Cloud Era: Trends, Tools, and Best Practices. *Scientia. Technology, Science and Society*, *2*(11), 310-318.

Malinowska, M. (2022). The concept of decision support system to increase the level of sustainable warehousing. *Procedia Computer Science*, *207*, 4046-4054.

Nakaguchi, V. M., & Ahamed, T. (2024). Deep learning algorithms for postharvest quality assessment: a new sensing methodology for quail eggs freshness estimation and shelf-life revalidation. In *IoT and AI in Agriculture: Smart Automation Systems for increasing Agricultural Productivity to Achieve SDGs and Society 5.0* (pp. 453-480). Singapore: Springer Nature Singapore.

Ojadi, J. O., Odionu, C., Onukwulu, E., & Owulade, O. A. (2024). Big data analytics and AI for optimizing supply chain sustainability and reducing greenhouse gas emissions in logistics and transportation. *International Journal of Multidisciplinary Research and Growth Evaluation*, *5*(1), 1536-1548.

Onyeaka, H., Tamasiga, P., Nwauzoma, U. M., Miri, T., Juliet, U. C., Nwaiwu, O., & Akinsemolu, A. A. (2023). Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and minimising environmental impact: A review. *Sustainability*, *15*(13), 10482.

Pandey, A. (2021). Food wastage: Causes, impacts and solutions. *Sci. Herit. J*, *5*(1), 17-20. [3]

Rokhva, S., & Teimourpour, B. (2025). Artificial intelligence in the food industry: food waste estimation based on computer vision, a brief case study in a University Dining Hall. *arXiv preprint arXiv:2507.14662*.

Shekhawat, S. (2023). Smart retail: How AI and IoT are revolutionising the retail industry. *Journal of AI, Robotics & Workplace Automation*, *2*(2), 145-152.

Theodoridis, G., & Tsadiras, A. (2024). Retail demand forecasting: A multivariate approach and comparison of boosting and deep learning methods. *International Journal on Artificial Intelligence Tools*, *33*(04), 2450001.

Tiwari, T., Garg, T., Singh, G., Mishra, S., & Guleria, K. (2024). Optimizing Food Utilization: A Smart Inventory Management and AI-Predictive Analytics in Reducing Food Waste. *International Journal of Science and Social Science Research*, *2*(3), 165-170.

Winkelmann, D., Ulrich, M., Römer, M., Langrock, R., & Jahnke, H. (2022). Dynamic stochastic inventory management in e-grocery retailing. *arXiv preprint arXiv:2205.06572*.

Zhou, C. (2024). Challenges and solutions in cross-platform mobile development: a qualitative study of Flutter and React Native. https://aaltodoc.aalto.fi/items/3ddc2600-0e11-4468-8747-17cf27c3d9aa