

Forecast Accuracy Versus Waste Outcomes: Evaluating AI Based Demand Forecasting in Perishable Food Retail

Octavia ALBU¹

Abstract

Food retailers increasingly adopt artificial intelligence (AI) and advanced analytics to improve forecasting and inventory management in perishable categories, often evaluating models mainly through standard accuracy metrics such as Mean Absolute Percentage Error (MAPE). This article argues that such symmetric metrics are insufficient when the managerial objective includes food waste reduction. Using daily sales data from three grocery stores and ten perishable product families in the Corporación Favorita dataset, the study compares a seasonal naïve benchmark with a Random Forest forecasting model. The models are evaluated with traditional accuracy measures, a safety-stock-based waste proxy, and asymmetric error metrics that emphasise over-forecasting. The results show that the seasonal naïve model achieves lower MAPE, yet the Random Forest model generates lower residual variability, lower safety stock, and a waste proxy approximately 20.7% below the benchmark, due to smaller over-forecast magnitudes. Additional analyses indicate that promotions and holidays systematically increase over-forecast errors for both models, but the Random Forest remains more robust in these high-risk periods. The findings suggest that AI-based forecasting can support waste reduction even when it does not improve conventional accuracy metrics, and that retailers should integrate waste-sensitive indicators into the evaluation and selection of forecasting systems.

Keywords: Food retail, Perishable products, Demand forecasting, Random Forest, Forecast accuracy, Food waste, Digitalization, Inventory management

JEL classification: C53, L81, Q18

DOI: 10.24818/RMCI.2026.2.205

1. Introduction

The food retail sector is undergoing a broad process of digital transformation driven by changing consumer expectations, technological advances, and growing pressure to improve both operational efficiency and sustainability (Nambisan et al., 2017; Gruia et al., 2020). In this environment, retailers increasingly rely on data analytics, automation, and artificial intelligence to optimize forecasting, replenishment, and inventory management (Nambisan et al., 2017; Onyeaka, 2023). These developments are especially important in perishable food categories, where managerial decisions must balance product availability

¹ Octavia Albu, Bucharest University of Economic Studies, e-mail: octavia.albu@fabiz.ase.ro

against the risk of spoilage, markdowns, and waste (Dash et al., 2019). At the same time, recent evidence shows that Romanian enterprises lag significantly behind the EU average in adopting AI, with an estimated 5.21% adoption rate compared with 19.95% across the Union (Shuleski, 2026)

Food waste has become a major economic, operational, and environmental challenge across the food supply chain, and the retail stage is particularly important because it links upstream supply decisions with final consumer demand (Lebersorger & Schneider, 2014). In food retail, inaccurate demand forecasts can lead directly to overstocking, excess safety stock, and avoidable waste, especially in short shelf-life categories such as dairy, meat, produce, seafood, and prepared foods. At the same time, retailers cannot simply minimize inventory, because under-forecasting may create stockouts and lost sales. As a result, forecasting in perishable retail is not only a technical prediction task, but also an operational decision problem in which different types of forecast errors have different business consequences.

There have been growing instances from the literature where digital technologies can help achieve sustainable retailing practices by helping to gain better visibility, better coordination, better forecasting capabilities, and even help in changing the whole business model into customer-centric and data-driven approaches. (Gruia et al., 2020; Dash et al., 2019). Artificial intelligence and machine learning are often presented as particularly promising because they can process large volumes of historical sales, promotional, and calendar data and identify patterns that may not be captured by simpler forecasting approaches (Kanade, 2022; Onyeaka, 2023). In practice, retailers also use such tools to support demand prediction, dynamic pricing, and stock rotation, all of which can reduce excess inventory and improve sustainability outcomes (Ghai, 2023). However, an important gap remains in the way forecasting models are evaluated. Most studies and business applications continue to rely heavily on standard accuracy metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). These measures are useful, but they treat over-forecasting and under-forecasting symmetrically, even though in perishable retail over-forecasting is often more harmful because it increases the likelihood of unsold stock becoming waste. Consequently, a model that appears superior according to traditional forecasting metrics may not necessarily be the one that best supports waste reduction or inventory control.

Against this background, the present article examines the relationship between forecasting performance and waste-related inventory risk in perishable food retail. Using daily sales data from the Corporación Favorita dataset, the study compares a seasonal naïve benchmark with a Random Forest model (RF) for selected stores and perishable product families. The article aims to determine whether a machine learning forecasting model can improve waste-related outcomes even when it does not outperform a simple benchmark on conventional accuracy measures.

More specifically, the analysis is guided by the following research questions:

- RQ1: Does a Random Forest forecasting model reduce estimated waste-related inventory risk compared with a seasonal naïve model in perishable retail categories?
- RQ2: Do standard symmetric accuracy metrics and waste-oriented evaluation metrics lead to different conclusions about model performance?
- RQ3: How do promotions and holidays affect over-forecast errors, and is the Random Forest model more robust than the seasonal naïve benchmark under these demand conditions?

The contribution of the article is twofold. First, it extends the evaluation of forecasting models beyond conventional accuracy metrics by incorporating a safety-stock-based waste proxy and asymmetric error measures that reflect the higher cost of over-forecasting in perishable categories. Second, it links forecasting performance to concrete retail conditions, namely promotions and holidays, showing how model quality depends not only on average accuracy but also on the operational context in which predictions are used. In doing so, the article contributes to the literature on digitalization in food retail by showing that the value of artificial intelligence should be assessed not only by predictive precision, but also by its capacity to support more sustainable and operationally effective decisions (Nambisan et al., 2017). This perspective aligns with more general theories of sustainability, where change is seen as the key element behind sustainable development, with an emphasis on shifting from simple prediction about the future to actually creating a better future through institutional decisions (Curaj et al., 2020), through directed institutional choices, including organisational practices that embed sustainability into core processes and treat employees as strategic resources for sustainable, competitive business (Munteanu et al., 2020).

2. Literature review

The retail business model, pivotal in bridging the gap between production and consumption, operates under a unique set of challenges and opportunities. Retailers in the food industry not only navigate the complexities of supply chain logistics and consumer preferences but also grapple with pressing issues like food waste management and sustainability. The efficiency of this model has significant implications not just for economic success, but also for environmental impact and societal well-being.

A food retailer is generally defined as a business or entity that sells food products directly to consumers, excluding restaurants (Pinho et al., 2018). This category includes supermarkets, hypermarkets, small grocery stores, specialty food shops, convenience stores and online grocery platforms. As the last stage before food reaches households, retailers mediate between upstream supply conditions and downstream demand and are therefore exposed to both operational pressures and sustainability expectations, particularly in relation to food waste.

Digitalisation in the food retail industry refers to the implementation of advanced digital technologies across key activities such as ordering, inventory management, pricing, marketing, fulfilment and customer interaction, with the aim of better meeting customer needs, streamlining operations and supporting more sustainable outcomes (Nambisan et al., 2017; Antineskul, 2022). The COVID-19 pandemic accelerated this process. Social distancing measures, lockdowns and heightened concerns for hygiene pushed consumers towards online grocery shopping and home delivery services, forcing retailers to rapidly extend or reconfigure their digital channels to survive, not merely to thrive (Muruganandam & Priyadharshini, 2022). For many operators, the pandemic represented a structural break that transformed operating models and made digital capabilities a condition for competitiveness.

At the same time, consumer behaviour remains heterogeneous. According to a 2022 global survey, around 60% of respondents still prefer to buy groceries in brick-and-mortar stores rather than online (Clifton, 2022). Many shoppers value the ability to inspect and select fresh produce and other perishable items, and they associate in-store shopping with sensory experiences and immediate gratification. The same survey shows that preferences vary by age: younger adults use online and physical channels in roughly equal measure, while older consumers show a stronger preference for in-store shopping; however, online grocery adoption is expected to grow over time (Clifton, 2022). For food retailers, this pattern implies that digitalisation must complement rather than replace physical formats, creating a need for integrated, omnichannel strategies.

Recent analyses identify several drivers of digital transformation in retail, including changing consumer expectations, technological innovation and environmental and regulatory pressures (Edsall et al., 2023). These drivers affect markets, business models and operational processes by reshaping how grocery businesses interact with customers and how they organise their supply chains. From new technologies such as natural language processing and predictive analytics to social changes and sustainability concerns, the combination of these forces creates a dynamic landscape in which traditional models must adapt (Nambisan et al., 2017). Understanding and leveraging these drivers has become essential for food retailers that seek long-term success and resilience.

One key aspect of digital transformation is the integration of digital technologies into core operational processes. This includes the automation of routine tasks, use of data analytics for informed decision-making, and real-time tracking and monitoring across the supply chain (Nambisan et al., 2017). By collecting, processing and interpreting large data streams from point-of-sale systems, online platforms, loyalty programmes and external sources, retailers can better understand demand patterns, adjust ordering and replenishment, and coordinate logistics activities. Digital tools thus have the potential to enhance operational efficiency, reduce costs and support more responsive and flexible business models (Manjula et al., 2021). However, technology alone is not sufficient. For digital transformation to be effective, food retailers need appropriate

management systems and organisational capabilities (Antineskul, 2022). This includes integrating digital tools into communication and coordination processes, rethinking workflows and roles, and investing in training programmes that develop employees' digital competencies. Without such capabilities, the potential benefits of advanced technologies may not translate into improved performance.

The evolution of food retail models illustrates these trends. Historically, retailers have shifted from full-service counter formats to self-service supermarkets, and later to large-scale hypermarkets. More recently, digitalisation has enabled new formats and experiences, including online grocery, "click and collect", and hybrid models that combine in-store shopping with digital tools. By making better use of data and automating processes, retailers aim to move towards more agile and responsive business models, able to adapt to changes in demand and supply more quickly than in the past. A central element of this evolution is the adoption of omnichannel strategies. In an omnichannel configuration, food retailers unify information and products across online and offline channels so that customers experience a consistent offer regardless of the access point (Chen et al., 2022). Information integration ensures that product data, prices and promotions are synchronised, while business integration links order fulfilment, inventory management and logistics between channels. Service and distribution integration, including last-mile delivery options, supports a smooth customer journey and efficient operations. Micro-fulfilment centers and dark stores are concrete examples: these dedicated spaces for online orders use combinations of warehouse robots and human workers to prepare orders quickly and accurately and can be located either in separate facilities or within existing stores (Begley et al., 2021). Such systems increase productivity and provide flexibility, but they also intensify the need for accurate demand forecasting and precise inventory management, particularly for perishable products.

Against this backdrop of a more connected technological ecosystem, tackling food waste has become one of the key goals, with the use of cutting-edge technologies such as blockchain technology, artificial intelligence, machine learning, intelligent packing, and other food waste technologies increasingly common across the food supply chain to deliver tamper-proof documentation regarding the origin, location, and expiry dates of goods for effective inventory control (Dash et al., 2019; Rodeck, 2023). Artificial intelligence and machine learning offer complementary capabilities. AI replicates certain human cognitive tasks by identifying patterns and learning from data, while machine learning specifically uses algorithms to learn from experience and make predictions without explicit programming (Kanade, 2022). In food retail, these technologies are increasingly used to analyse large volumes of sales, weather and calendar data to predict demand more accurately and thus avoid both overstocking and stockouts (Onyeaka et al., 2023). AI-based forecasting and replenishment systems can recommend order quantities that better match expected sales, particularly in perishable categories where mistakes quickly translate into waste. Dynamic pricing is another digital tool for reducing waste by lowering prices as products approach

their best-before dates, encouraging sales and limiting spoilage; integrated with forecasting and inventory systems, it helps align replenishment, pricing and waste objectives (Ghai, 2023).

The existing literature thus shows that digitalisation and AI can support more efficient and sustainable operations in food retail, including the reduction of food waste. However, much of this work focuses on describing technologies and their potential applications, and comparatively less attention is paid to how forecasting models are evaluated in a way that aligns with waste-related objectives. Forecasting studies often report symmetric accuracy metrics, such as Mean Absolute Percentage Error or Root Mean Squared Error, which do not differentiate between over- and under-forecasting and do not directly capture the inventory implications of errors (Onyeaka et al., 2023). In perishable categories, this is a critical gap, because over-forecasting can be more damaging than under-forecasting when it leads to excess inventory that cannot be sold in time.

However, most AI-oriented forecasting studies in domains such as energy finance evaluate models almost exclusively through statistical error measures, with limited attention to how different models translate into operational or sustainability-related impacts (Anagnoste et al., 2025).

By explicitly contrasting MAPE with proxies for food waste, this analysis contributes to this emerging literature by re-anchoring model comparison in the objectives of retailers and sustainability policy. Within this context, the present article narrows the focus to the evaluation of demand forecasting models for perishable food retail. Building on the literature on digital transformation, AI adoption and waste reduction, it examines how different forecasting approaches behave when assessed using indicators that explicitly reflect waste-relevant inventory risk, including residual variability, safety stock and asymmetric measures of over-forecasting.

3. Methodology

3.1 Research design

This study uses a quantitative, comparative design to examine how different demand forecasting models affect waste relevant inventory risk in perishable grocery categories. Two models are evaluated on the same data: a seasonal naïve benchmark and a Random Forest regression model. Instead of relying only on standard accuracy measures, the evaluation links forecast errors to indicators that approximate food waste exposure and penalise over forecasting more strongly than under forecasting.

3.2 Data and empirical scope

The empirical analysis uses the Corporación Favorita daily sales dataset for grocery stores in Ecuador. The main file reports, for each date, store, and product

family, the number of units sold and the number of items under promotion, while additional files provide store characteristics and a holiday calendar.

To balance heterogeneity and interpretability, the sample is restricted to three stores (two in Quito with different formats and one in Salinas) and ten perishable product families (bread/bakery, dairy, deli, meats, poultry, seafood, produce, eggs, frozen foods, prepared foods). The unit of analysis is the store–product family–day, with sales aggregated to this level. The observation window is the calendar year 2016, which provides one full seasonal cycle and avoids complications from structural changes over multiple years.

3.3 Variable construction

For the Random Forest model, the feature set captures recent demand dynamics, calendar effects, and promotions:

- Lagged sales: sales on the previous day (lag1), same weekday one week earlier (lag7), and two weeks earlier (lag14)
- Rolling statistics: 7 day rolling mean and 7 day rolling standard deviation of sales
- Calendar variables: day of week, month, and a holiday indicator
- Promotions: number of items on promotion and a binary promotion flag.

All lagged and rolling features are computed separately within each store–product family series, sorted by date, so only past information from the same series is used and no information leaks across stores, categories, or future periods.

3.4 Forecasting models and estimation

The seasonal naïve model exploits weekly seasonality by predicting demand for day t with observed demand from the same weekday in the previous week:

$$\hat{y}_t = y_{t-7} \quad (1)$$

This provides a simple, transparent benchmark suitable for grocery data with strong weekly patterns.

The Random Forest regressor models a non-linear mapping from predictors X_t to sales:

$$\hat{y}_t = f(X_t) \quad (2)$$

where f is learned from an ensemble of decision trees fitted on bootstrap samples and random subsets of predictors. This structure allows the model to capture interactions and non-linear effects of promotions, holidays, and recent demand without specifying a parametric form.

Because forecasting is time dependent, the data are split chronologically. Observations from January-October 2016 form the training period, and November-December 2016 form the test period, mirroring the practical use of historical data to forecast future demand and avoiding optimistic bias from random splits. The

models are evaluated using three complementary groups of metrics: symmetric accuracy, a safety stock-based waste proxy, and asymmetric error measures focused on over forecasting.

3.5 Symmetric accuracy

Standard metrics provide a familiar baseline:

- Mean Absolute Percentage Error (MAPE) summarises average proportional error.
- Root Mean Squared Error (RMSE) penalises large deviations by squaring errors before averaging.

Both treat over and under forecasting symmetrically and do not directly reflect inventory or waste outcomes. Similar combinations of exponential smoothing, seasonal ARIMA and neural network autoregression have been used to compare forecasting performance on macroeconomic series such as the Romanian unemployment rate, with evaluation based on RMSE, MAE and MAPE (Davidescu et al., 2021).

3.5 Safety-stock-based waste proxy

To approximate waste relevant risk, forecast residuals are defined as:

$$e_t = y_t - \hat{y}_t \quad (3)$$

Their standard deviation over the test period is interpreted as demand uncertainty conditional on a model. Safety stock is approximated as 1.65 times the standard deviation of forecast errors, which corresponds to a 95% service level.

Because actual waste quantities are not observed, expected waste is taken to be 5% of safety stock, representing a plausible shrink rate for perishables. The percentage waste reduction achieved by the Random Forest relative to the baseline is computed as:

$$\frac{Waste_{baseline} - Waste_{ML}}{Waste_{baseline}} \times 100\% \quad (4)$$

This yields a consistent, assumption-based comparison of waste related risk rather than a direct measurement of physical waste.

3.6 Asymmetric error metrics and context

Because over forecasting drives excess inventory, additional metrics focus on positive errors. Over-forecast error is defined as the amount by which the forecast exceeds actual demand on a given day; negative errors are set to zero so that only over-predictions are counted. For each model, the analysis computes:

- Over forecast rate: share of test days on which the forecast is above the realised demand.
- Average over forecast magnitude: mean $OverError_t$ on days with over forecasting.

- Total over forecast volume: sum of $OverError_t$ over the test period.

Pinball loss with $\tau = 0.3$ is also used to encode asymmetric costs, penalizing over forecasting more than under forecasting in line with higher waste costs in perishable categories.

Finally, the study examines how promotions and holidays affect over forecast errors. For each day, it defines binary indicators for promotion and holiday status and a continuous promotion intensity variable. It then (a) compares over forecast statistics across conditions, (b) uses t tests to assess differences in mean over errors, and (c) estimates linear regressions of over forecast error on promotion, holiday, and promotion intensity indicators for each model separately. This context sensitive analysis reveals whether the machine learning model is more robust to demand shocks that are particularly relevant for waste.

4. Results and discussion

Table 1 reports the performance of the seasonal naïve and Random Forest models on the test period (November–December 2016), using standard symmetric accuracy and the safety stock-based waste proxy.

Forecast accuracy and waste proxy indicators

Table 1

Model	MAPE (%)	Safety stock estimate	Estimated waste
Seasonal naïve	37.69	1015.82	50.79
Random Forest	42.77	805.67	40.28

Source: author’s own research results.

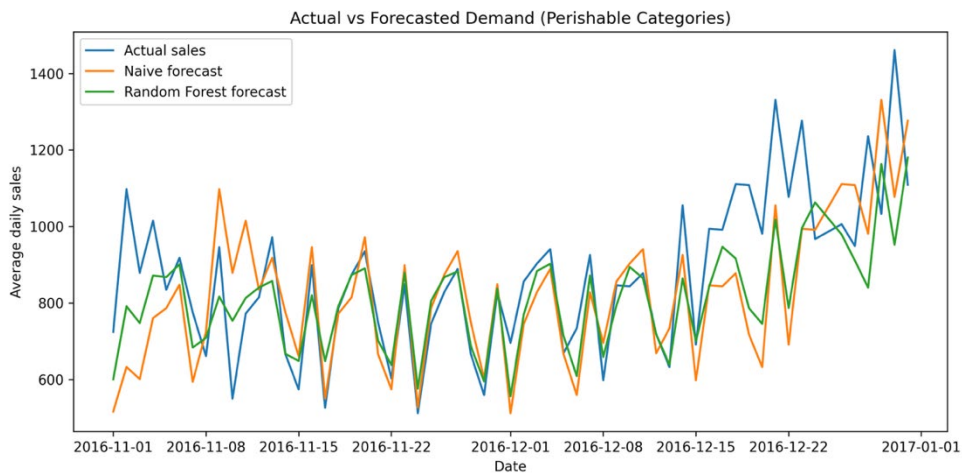


Figure 1. Actual versus forecasted demand

Source: author’s own research results.

The seasonal naïve model records a lower MAPE (37.69%) than the Random Forest model (42.77%), indicating superior average proportional accuracy according to a standard forecasting metric. This is consistent with the models' design, as the seasonal naïve specification directly exploits weekly patterns that are strong in grocery sales. By contrast, the Random Forest model achieves a lower safety stock estimate (805.67 versus 1015.82) and a lower value of the waste proxy (40.28 versus 50.79). Under the common service level and waste rate assumptions, this implies an estimated waste reduction of approximately 20.7% relative to the seasonal naïve benchmark. The results therefore show that the model with better MAPE performance is not necessarily the one with lower waste related inventory risk. There is further evidence to support the fact that simple seasonal indices have performed satisfactorily in forecasting classical accuracy measures compared to flexible models, but the latter tend to dominate when forecasts are based on decision-relevant criteria (Davidescu et al., 2021).

To reflect the higher operational cost of over forecasting for perishable goods, the models are also evaluated using asymmetric metrics focused on the frequency and magnitude of positive errors, as well as pinball loss with stronger penalties on over forecasting.

Asymmetric error metrics

Table 2

Model	Over forecast rate (%)	Avg over forecast magnitude	Pinball loss ($\tau = 0.3$)
Seasonal naïve	45.6	199.06	105.80
Random Forest	50.9	122.18	79.37

Source: author's own research results.

The seasonal naïve model over forecasts in 45.6% of test observations, while the Random Forest model over forecasts in 50.9% of cases. On this dimension alone, the benchmark appears preferable, since it predicts demand above actual sales less frequently. However, when the models do over forecast, the average magnitude of the positive error is substantially larger for the seasonal naïve model (199.06 units) than for the Random Forest (122.18 units). In other words, the Random Forest model generates more frequent but smaller over predictions, while the seasonal naïve model produces fewer but larger deviations.

This pattern is reflected in the pinball loss values. With an asymmetric loss parameter of 0.3, which penalizes over forecasting more heavily than under forecasting, the Random Forest model records a lower loss (79.37) than the seasonal naïve model (105.80). When the evaluation is aligned with the higher cost of excess inventory, the Random Forest is therefore preferable, despite its higher MAPE. The results underline that, for waste related outcomes, the magnitude of over forecasting errors is more consequential than their frequency alone.

The next step is to assess whether promotions systematically affect over forecast errors and whether the two models respond differently to such conditions. Table 3 presents the main statistics for promotion and non-promotion days.

Over forecast errors by promotion status

Table 3

Model	Condition	Obs.	Avg over error	Median over error	Total over error	Over-forecast rate (%)
Naïve	No promotion	1230	74.78	0.00	91,977.30	43.98
	Promotion	570	125.00	0.00	71,250.21	48.95
RF	No promotion	1230	49.98	0.00	61,479.19	49.35
	Promotion	570	88.48	5.65	50,436.37	54.21

Source: author's own research results.

For both models, the average over forecast error is higher on promotion days than on non-promotion days. For the seasonal naïve model, the mean over error increases from approximately 60.8 units on non-promotion to 100.7 units during promotions. For the Random Forest model, the increase is from 45.4 to 67.8 units. This indicates that promotions are associated with greater waste relevant error magnitudes, irrespective of model choice. Comparing across models, the Random Forest consistently exhibits lower average over errors in both conditions, as well as a lower total over forecast volume during promotions. Although its over forecast rate is slightly higher, the individual positive errors are smaller on average. Independent sample t tests confirm that the differences between promotion and non-promotion days are statistically significant for both models, suggesting that promotions systematically shift error distributions toward higher over estimation.

A similar analysis is conducted for holidays. Table 4 reports the main indicators for holiday and non-holiday:

Over forecast errors by holiday status

Table 4

Model	Condition	Obs.	Avg over error	Median over error	Total over error	Over-forecast rate (%)
Naïve	No holiday	1230	74.78	74.78	0.00	91,977.30
	Holiday	570	125.00	125.00	0.00	71,250.21
RF	No holiday	1230	49.98	49.98	0.00	61,479.19
	Holiday	570	88.48	88.48	5.65	50,436.37

Source: author's own research results.

For both forecasting models, average over forecast errors are higher on holidays than on non-holiday days. The seasonal naïve model's mean over error rises from 74.78 units to 125.00 units, while the Random Forest model's mean over error increases from 49.98 units to 88.48 units. The effect of holidays is larger than that of promotions, indicating that holidays create more pronounced disruptions in demand patterns.

Again, the Random Forest model maintains lower average and total over errors in both conditions, despite a higher over forecast rate. T tests show that the

differences between holiday and non-holiday periods are statistically significant, confirming that holidays are a critical context for waste relevant forecast errors.

To jointly assess the influence of promotions, holidays, and promotion intensity on over forecast errors, a linear regression model is estimated separately for each forecasting method:

$$\begin{matrix} \text{OverError}_t = \beta_0 + \beta_1 \text{Promotion}_t + \beta_2 \text{Holiday}_t + \beta_3 \text{OnPromotion}_t + \\ \varepsilon_t \end{matrix} \quad (5)$$

The regression results indicate that the coefficients associated with holiday status and promotion intensity are positive and statistically significant for both models, implying that holidays and higher numbers of promoted items are linked to larger over forecast errors. For the seasonal naïve model, both the binary promotion indicator and the promotion intensity variable tend to have significant positive effects, whereas for the Random Forest model, the promotion intensity effect remains strong while the binary promotion indicator is weaker.

In both cases, holiday effects are economically and statistically larger than promotion effects, which aligns with the descriptive statistics in Tables 3 and 4. The regression evidence therefore confirms that promotions and holidays systematically increase waste relevant forecast errors, and that the Random Forest model, while not immune, attenuates these effects compared with the seasonal naïve benchmark.

5. Conclusions

This paper examined how the evaluation of demand forecasting models in food retail changes when the focus shifts from traditional accuracy metrics towards waste relevant operational indicators. Using daily sales data for perishable product families in three grocery stores, the analysis compared a seasonal naïve benchmark with a Random Forest model under identical data and assumptions. While the seasonal naïve model outperformed the Random Forest in terms of Mean Absolute Percentage Error, the Random Forest generated lower residual variability, lower safety stock estimates, and a lower waste proxy, corresponding to an estimated reduction in waste exposure of about one fifth relative to the benchmark. Additional analyses based on asymmetric error metrics and event specific conditions (promotions and holidays) confirmed that the machine learning model better contained the magnitude of over forecasting errors, even though it over forecast slightly more often.

Taken together, these findings support the central argument of the paper: evaluating forecasting models for perishable food retail exclusively on symmetric accuracy measures such as MAPE can be misleading from a sustainability perspective. What matters for food waste is not only how large the average proportional error is, but how volatile the errors are and how big the positive errors become in high-risk periods. A model that produces more stable, smaller over forecasting errors may be operationally superior, even if its traditional accuracy is weaker. From a broader

management viewpoint, this result aligns with the literature on digitalization and analytics in retail, which suggests that the value of advanced technologies depends on how closely their performance criteria are aligned with actual business objectives, in this case the reduction of avoidable food waste.

The empirical results have several implications for food retailers and for managers responsible for digital transformation and sustainability initiatives. First, the study suggests that retailers should expand their model evaluation dashboards beyond standard accuracy metrics to include waste sensitive indicators such as residual variability, safety stock requirements, and asymmetric loss measures that penalize over forecasting more strongly than under forecasting. This kind of multi-dimensional evaluation can prevent situations where a technically “accurate” model unintentionally increases excess inventory and waste. The findings also underline the importance of paying particular attention to promotions and holidays when deploying forecasting models in perishable categories. Both events were associated with systematically higher over forecast errors, and the holiday effect was especially strong. Retailers can use this insight to design differentiated forecasting and replenishment policies for these periods, for example by tightening over forecasting tolerances, adjusting safety stock factors, or combining machine learning forecasts with managerial overrides informed by local knowledge of demand spikes.

The paper contributes to the ongoing discussion about the role of artificial intelligence in retail operations. They show that relatively accessible machine learning methods, such as Random Forests, can contribute to waste reduction, if they are evaluated against the right criteria and embedded in decision processes that recognize the asymmetry between excess and shortage costs. For retailers investing in digital competencies and data analytics capabilities, this implies that algorithm design, several limitations of the study should be acknowledged. The first concerns the measurement of waste. The analysis relies on a safety stock-based proxy that assumes a fixed service level and waste rate; actual disposals, markdowns, and shrinkage are not observed in the dataset. The results therefore reflect comparative waste exposure under common assumptions, not an exact audit of physical waste volumes. Second, the empirical design uses product family level data rather than SKU level information. Within families such as produce or frozen foods, products differ in shelf life, demand variability, and waste patterns, which are not fully captured by aggregated series. A more granular dataset could reveal stronger or weaker effects for particular subcategories. Third, the sample is limited to three stores and one year of data, selected deliberately for interpretability rather than representativeness. Results may differ in other formats, regions, or time periods, especially where demand volatility or promotional practices are different. Finally, the modelling approach is intentionally modest. The Random Forest model used in the analysis is not heavily tuned and does not incorporate more advanced techniques such as gradient boosting, probabilistic forecasts, or joint optimization of inventory costs. This reinforces the transparency of the results but leaves open the question of how more complex models would perform under the same waste-oriented evaluation.

Future research could address these limitations and extend the current work in several directions. A first avenue is to obtain and analyse data that include actual waste quantities, markdowns, and stock out measures, allowing direct estimation of the link between forecast errors, inventory policies, and realized waste. This would enable structural models that jointly optimise forecasting, replenishment, and waste outcomes. A second direction is to move from product family to SKU level analyses and to incorporate category specific shelf life and cost parameters.

References

1. Anagnoste, S., Andrei, A-V., Bolovaneanu, V., Cepoi, C-O., Clodnitchi, R., Cramer, A-A., Grecu, R-A., Lessmann, S., Pele, D.T., Petukhina, A. & Strat, V.A., 2025. The role of AI in (re)shaping energy finance: A systematic literature review. *Energy Strategy Reviews*, 61, 101833. <https://doi.org/10.1016/j.esr.2025.101833>
2. Antineskul, E., 2022. The impact of digital transformation on the retail food business. *Horizons*, 30(1). <https://doi.org/10.20544/horizons.a.30.1.22.p12>
3. Begley, S., Chandra, V. & Gill, P., 2021. Automation opportunities in North American grocery. McKinsey & Company. Available at: <https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/automation-opportunities-in-north-american-grocery>
4. Chen, X., Su, X., Lin, W., Xu, A., Chen, J. & Zheng, Q., 2022. The effect of omnichannel integration on fresh food customer engagement from the viewpoint of flow experience. *Sustainability*, 14(21), 13914. <https://doi.org/10.3390/su142113914>
5. Clifton, M., 2022. Global consumers still prefer to buy groceries in person. YouGov. Available at: <https://business.yougov.com/content/44376-global-consumers-still-prefer-buy-groceries-person>
6. Curaj, A., Păunică, M., Popa, A., Holeab, C. & Jora, O-D., 2020. Sustainability through directed change in the visionary university: From predicting to producing the future. *Amfiteatru Economic*, 22(55), pp. 905-919. <https://doi.org/10.24818/EA/2020/55/905>
7. Davidescu, A.A., Apostu, S. & Paul, A., 2021. Comparative analysis of different univariate forecasting methods in modelling and predicting the Romanian unemployment rate for the period 2021-2022. *Entropy*, 23(3), 325. <https://doi.org/10.3390/e23030325>
8. Dash, R., McMurtrey, M., Rebman, C. and Kar, U., 2019. Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, 14(3), pp. 33-42. <https://doi.org/10.33423/jsis.v14i3.2105>
9. Edsall, D., Gray, C., Witherspoon, J., McDonnell, M. & Almond, A., 2023. Future of grocery retail. Deloitte Consumer Industry Center. Available at: <https://www2.deloitte.com/us/en/insights/industry/retail-distribution/future-of-grocery-retail.html>
10. Ghai, N., 2023. Why grocers must adopt dynamic pricing for growth and customer satisfaction. *Grocery Doppio*. Available at: <https://www.grocerydoppio.com/articles/why-grocers-must-adopt-dynamic-pricing-for-growth-and-customer-satisfaction>
11. Gruia, L-A., Bibu, N., Năstase, M., Roja, A. & Cristache, N., 2020. Approaches to digitalization within organizations. *Review of International Comparative Management*, 21(3), pp. 287-297. <https://doi.org/10.24818/RMCI.2020.3.287>
12. Lebersorger, S., & Schneider, F. (2014). Food loss rates at the food retail, influencing factors and reasons as a basis for waste prevention measures. *Waste Management*, 34(11), 1911-1919. <https://doi.org/10.1016/j.wasman.2014.06.013>

13. Kanade, V., 2022. What is machine learning? Understanding types & applications. Spiceworks. Available at: <https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-ml/>
14. Manjula, S., Balaji, P., Deepa, N. & Vidhyavathi, A., 2021. Digital transformation on food retail industries – A review. *Asian Journal of Agricultural Extension, Economics and Sociology*, 39(11), pp. 88-101. <https://doi.org/10.9734/ajaees/2021/v39i1130729>
15. Munteanu, A-I., Bibu, N., Năstase, M., Cristache, N. & Matis, C., 2020. Analysis of practices to increase the workforce agility and to develop a sustainable and competitive business. *Sustainability*, 12(9), 3545. <https://doi.org/10.3390/su12093545>
16. Muruganandam, S.S. & Priyadharshini, P., 2022. Customer preference towards online grocery shopping. *International Journal of Creative Research Thoughts (IJCRT)*, 10(7), pp. 196-200.
17. Nambisan, S., Lyytinen, K., Majchrzak, A. & Song, M., 2017. Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1), pp. 223-238. <https://doi.org/10.25300/MISQ/2017/41.1.03>
18. 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.
19. Pinho, M., Mackenbach, J., Oppert, J., Charreire, H., Bárdos, H., Rutter, H. et al., 2018. Exploring absolute and relative measures of exposure to food environments in relation to dietary patterns among European adults. *Public Health Nutrition*, 22(6), pp. 1037-1047. <https://doi.org/10.1017/S1368980018003063>
20. Rodeck, D., 2023. What is blockchain? *Forbes Advisor*. Available at: <https://www.forbes.com/advisor/investing/cryptocurrency/what-is-blockchain/>
21. Shuleski, D. (2026). A comparative analysis of artificial intelligence adoption rates: Romania vs. the European Union (2024–2026). *Review of International Comparative Management*, 27(1), 113-122. <https://doi.org/10.24818/RMCI.2026.1.113>