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Optimising Grocery Retail Pricing Through Demand Forecasting, Product Expiry Analytics and Customer Price Sensitivity Modelling

Jumoke Eniola Famoroti

Area Manager, Pawatank, Nigeria

ABSTRACT

Grocery retail pricing has become increasingly complex due to fluctuating consumer demand, rising operational costs, competitive pressures, and substantial losses associated with perishable inventory. Conventional pricing strategies frequently overlook interactions between purchasing behaviour, product shelf life, and demand variability, resulting in inefficient markdown decisions, inventory waste, and reduced profitability. This study proposes an integrated analytical framework combining demand forecasting, product expiry analytics, and customer price sensitivity modelling to optimise grocery retail pricing decisions. Historical sales transactions, inventory records, promotional activities, product expiration dates, and customer purchasing patterns provide the analytical foundation. Machine learning forecasting models estimate product demand across temporal and seasonal conditions, while expiry risk indicators quantify remaining shelf life and potential spoilage exposure. Price elasticity estimation captures heterogeneous customer responses to price adjustments, enabling differentiated markdown strategies across product categories and consumer segments. A constrained optimisation model subsequently integrates demand predictions, expiry probabilities, and elasticity estimates to recommend prices that balance revenue generation, inventory turnover, and waste reduction. The proposed framework offers a systematic approach to improving pricing responsiveness, strengthening operational efficiency, and supporting economically sustainable grocery retail management across diverse market conditions and retail environments.

Keywords: Grocery Retail Pricing; Demand Forecasting; Product Expiry Analytics; Price Elasticity Modelling; Dynamic Markdown Optimisation; Perishable Inventory Management.

1. INTRODUCTION

1.1 Grocery Retail Pricing Pressures and Perishable Inventory Challenges

Grocery retail operates within a highly competitive environment characterised by narrow profit margins, fluctuating wholesale costs, changing consumer preferences, and continuous pricing pressures [1]. Retailers must balance revenue generation, inventory availability, and customer affordability while responding to seasonal demand and competitor promotions [2]. Perishability introduces additional complexity because fresh produce, dairy, meat, bakery products, and chilled foods possess limited commercial lifespans. As expiration approaches, declining product value increases the likelihood of unsold inventory, forcing retailers to choose between maintaining regular prices, introducing markdowns, or absorbing spoilage losses [3]. Consumer price sensitivity, promotional intensity, seasonal purchasing patterns, and stock availability further influence purchasing behaviour and product substitution [4]. Poorly coordinated pricing decisions may consequently reduce gross margins, accelerate inventory deterioration, increase food waste, and weaken customer satisfaction. Effective grocery pricing therefore requires coordinated consideration of demand uncertainty, remaining shelf life, inventory conditions, and consumers' responses to changing prices [5].

1.2 Limitations of Conventional Grocery Pricing and Markdown Strategies

Conventional grocery pricing frequently relies on cost-plus calculations, competitor price matching, fixed-percentage markdowns, and manually scheduled promotional campaigns [2]. Although operationally straightforward, these approaches often overlook product-specific demand patterns, remaining shelf life, available stock, and differences in consumer price responsiveness [5]. Standardised discounts may therefore generate insufficient demand for highly perishable inventory while unnecessarily reducing margins on products likely to sell without intervention [6]. Historical sales averages also provide incomplete demand estimates when promotional activities, stockouts, seasonal fluctuations, and substitution effects distort observed purchasing behaviour. Furthermore, excessive markdowns can erode profitability, encourage customers to postpone purchases, and shift demand away from regularly priced alternatives [7]. Existing operational approaches frequently address forecasting, inventory expiry, and pricing decisions independently, limiting their ability to capture interactions between these variables. This fragmentation establishes the need for integrated analytical methods combining demand prediction, expiry-related inventory assessment, and price elasticity estimation to support commercially sustainable markdown decisions [8].

1.3 Research Aim, Objectives and Proposed Contributions

This study proposes an integrated data-driven grocery pricing framework combining demand forecasting, product expiry analytics, and customer price sensitivity estimation to support adaptive markdown decisions [3]. The principal objectives are to predict product-level demand, quantify inventory exposure to expiration, estimate price elasticity, and optimise selling prices under operational constraints [6]. The framework seeks to improve gross margins, increase inventory sell-through, reduce expired stock, and strengthen inventory allocation efficiency while maintaining customer affordability [7]. Its proposed contribution involves linking predictive demand models with shelf-life information and empirically estimated price responses within a unified optimisation architecture. Conventional cost-plus pricing, fixed markdown schedules, and competitor-based strategies will provide comparative benchmarks, supported by independent model validation and sensitivity analysis [8]. Practical implementation will emphasise interpretable pricing recommendations, operational feasibility, and safeguards against excessive or inconsistent discounts. Subsequent sections examine theoretical foundations, data acquisition, feature engineering, predictive modelling, optimisation methods, and performance evaluation across perishable grocery categories [5].

2. GROCERY PRICING ECONOMICS AND ANALYTICAL FOUNDATIONS

2.1 Demand Dynamics and Price Formation in Grocery Retail

Grocery demand reflects interactions among retail prices, household purchasing behaviour, promotional incentives, seasonal conditions, and competing product alternatives [6]. Regular-price demand generally represents established consumption patterns, whereas promotional demand may incorporate temporary stockpiling, accelerated purchases, and switching between brands or retailers [7]. Demand responsiveness also varies across product categories. Staple goods frequently exhibit relatively stable consumption requirements, while discretionary products and highly perishable items may experience stronger fluctuations associated with pricing and freshness [8]. Cross-product substitution occurs when consumers replace increasingly expensive products with cheaper alternatives, whereas complementary purchasing links demand across jointly consumed items. These relationships complicate sales forecasting because price changes influence both product-level demand and category allocation [9]. Consequently, demand estimation must explicitly condition expected sales on proposed prices, promotional conditions, inventory availability, and relevant market characteristics rather than treating demand as independent of pricing decisions [10].

2.2 Product Expiry, Shelf-Life Deterioration and Inventory Economics

Perishable inventory management requires continuous consideration of remaining shelf life, batch-specific expiration dates, replenishment schedules, and declining commercial freshness [7]. First-expiring-first-out rotation prioritises older eligible inventory, reducing the likelihood that newer deliveries are sold while earlier batches deteriorate. Physical expiration, legally applicable sale restrictions, and consumer freshness preferences represent distinct constraints that influence product marketability [10]. Replenishment frequency, supplier lead times, delivery reliability, and existing stock quantities determine the period available for selling inventory before deterioration becomes economically significant. Unsold products generate direct losses through inventory write-offs, disposal expenditure, and foregone contribution margins [11]. As expiration approaches, the expected value of maintaining regular prices must be compared with potential sales generated through discounts. Optimal markdown timing therefore depends on remaining inventory, forecast demand, price responsiveness, and the probability of spoilage under alternative pricing decisions [12].

2.3 Customer Price Sensitivity and Demand Elasticity

Own-price elasticity measures the percentage change in quantity demanded associated with a one-percent change in product price, holding other relevant demand determinants constant [8]. It provides an economic basis for estimating whether markdown-induced sales increases can compensate for reduced unit margins. Consumer responsiveness differs across grocery categories, store locations, household purchasing characteristics, and promotional environments [11]. Loyalty programme records, transaction histories, and observed purchasing patterns may support estimation of heterogeneous price responses, provided appropriate privacy safeguards are maintained. However, observed price–sales correlations do not necessarily represent causal demand relationships because retailers frequently adjust prices in anticipation of changing demand [12]. Promotional targeting, stockouts, seasonal variation, and competitor actions introduce additional endogeneity and confounding. Reliable elasticity estimation therefore requires suitable identification strategies, including controlled price experiments or defensible quasi-experimental methods [13]. Estimates should include uncertainty intervals and remain applicable primarily within observed price ranges, avoiding unsupported extrapolation to extreme discounts [14].

2.4 Integrated Pricing Decisions and Retail Performance Trade-offs

Integrated grocery pricing combines conditional demand forecasts, estimated price elasticity, remaining shelf life, and available inventory to determine commercially appropriate selling prices [10]. Retailers must balance gross margin, sales volume, inventory sell-through, waste reduction, and customer affordability under competing operational objectives [12]. Revenue maximisation alone may encourage excessive discounting, overlook disposal costs, or create undesirable customer pricing outcomes. Constrained optimisation provides a structured approach for selecting prices subject to margin requirements, stock availability, legal restrictions, and acceptable markdown limits [13]. The resulting framework links demand uncertainty, expiry

exposure, and consumer responsiveness to measurable retail performance, establishing the conceptual foundation for subsequent empirical modelling [14].

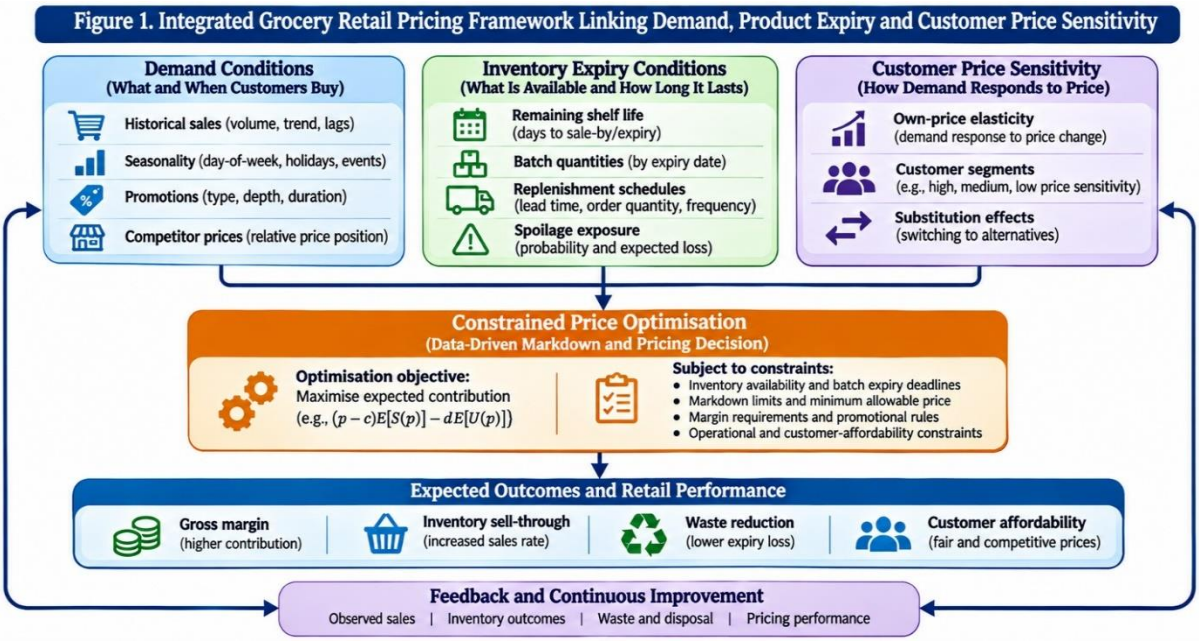


Figure 1. Integrated grocery retail pricing framework linking demand, product expiry and customer price sensitivity.

The conceptual framework integrates three analytical branches: demand conditions, comprising historical sales, seasonality, promotions, and competitor prices; inventory expiry conditions, including remaining shelf life, batch quantities, replenishment schedules, and spoilage exposure; and consumer price sensitivity, represented by own-price elasticity, customer segments, and substitution effects. These inputs converge into a constrained price optimisation process that evaluates gross margin, inventory sell-through, waste reduction, and customer affordability. Feedback from observed sales, remaining stock, and realised markdown performance informs subsequent pricing decisions.

3. RESEARCH DESIGN AND MULTISOURCE DATA ACQUISITION

3.1 Retail Setting, Product Population and Sampling Design

The proposed study will examine grocery pricing operations across supermarkets, independent grocery stores, and multistore retail networks with documented sales and inventory histories [12]. The product population will include fresh produce, meat, dairy, bakery products, chilled foods, and selected packaged groceries, representing different perishability characteristics [13]. Store–product–day observations will support demand estimation, while store–product–batch records will enable expiry-sensitive inventory analysis where batch identifiers are available. Historical observations should cover at least one complete seasonal cycle, with forecasting horizons aligned to replenishment and remaining shelf life [14]. Product eligibility will require reliable pricing, transaction, and availability records. Store characteristics, assortment differences, and regional demand conditions will inform sampling and representativeness assessments. Products subject to regulated prices, contractual restrictions, or operationally fixed pricing will be distinguished from inventory eligible for dynamic markdown optimisation [15].

3.2 Historical Sales, Transaction and Pricing Data

Historical transaction data will be extracted from point-of-sale systems, incorporating product identifiers, transaction timestamps, quantities sold, realised selling prices, discounts, and promotional indicators [13]. Pricing databases will provide regular prices, temporary markdown schedules, campaign characteristics, and loyalty-related discount information. Store-level transaction frequencies and daily sales volumes will support demand reconstruction across products and observation periods [14]. Recorded sales will be distinguished from underlying demand because stockouts, limited shelf availability, and purchase restrictions can censor observed quantities. Inventory availability indicators will therefore accompany transaction records to identify periods when demand may exceed realised sales [16]. Returns, cancelled purchases, duplicate transactions, and inconsistent price entries will be flagged before aggregation. Product identifiers will be harmonised across point-of-sale, pricing, and inventory systems using validated stock-keeping units and store codes. Effective transaction prices will reflect actual customer payments after applicable discounts, excluding taxes where analytically appropriate [17].

3.3 Product Expiry, Inventory and Replenishment Records

Inventory data will include batch identifiers, delivery dates, expiry dates, received quantities, stock balances, and recorded inventory adjustments [14]. Replenishment records will capture supplier lead times, order quantities, delivery schedules, stock transfers, shrinkage, and disposal volumes. Shelf

inventory will be distinguished from backroom stock because physical availability influences purchasing opportunities and observed sales [15]. Batch-level visibility is particularly important when products with different expiration dates remain available simultaneously, creating heterogeneous markdown requirements. Markdown implementation timestamps and quantities exposed to each discount will be recorded to associate pricing decisions with relevant inventory [16]. Where point-of-sale systems cannot identify the batch sold, inventory depletion will be estimated using documented rotation assumptions, with uncertainty explicitly retained. Reconciliation of receipts, sales, transfers, and disposals will support stock-balance validation. These records will enable assessment of remaining shelf life, expected spoilage exposure, and replenishment-related pricing constraints [18].

3.4 Customer Price Sensitivity and Market Context Data — 130 Words

Customer purchasing information will be obtained from appropriately anonymised loyalty transactions and aggregated behavioural records, including purchase frequency, promotion participation, repeat purchases, and product substitution patterns [15]. Customer segments will be defined using observable purchasing characteristics rather than unsupported assumptions about demographic attributes. Competitor prices will be incorporated where collection is lawful, reliable, and operationally feasible [16]. External variables will include public holidays, weather conditions, local events, and relevant economic indicators affecting grocery expenditure. These contextual factors will help distinguish price responses from demand changes associated with seasonal conditions or market disruptions [17]. Potential confounders will include retailer anticipation of demand, targeted promotions, competitor actions, and concurrent assortment changes. Data minimisation, restricted access, pseudonymisation, and appropriate retention controls will protect customer information while supporting statistically meaningful estimation of heterogeneous purchasing behaviour [19].

3.5 Data Quality, Governance and Experimental Design

Data preparation will include duplicate removal, missingness assessment, timestamp verification, unit standardisation, and reconciliation across sales, pricing, and inventory systems [16]. Stock movements and markdown records will be checked against transaction histories to identify inconsistent quantities or implementation dates. Chronological training, validation, and independent testing periods will be established before model development to prevent temporal information leakage [17]. Historical pricing policies will provide observational benchmarks, although causal conclusions will require appropriate identification assumptions. Controlled price experiments or store-level pilots may be conducted where commercial, legal, and ethical conditions permit [18]. Documented access permissions, customer privacy safeguards, version-controlled extraction procedures, and reproducible data transformations will strengthen research governance and analytical transparency [19].

Table 1. Multisource Grocery Retail Data Inventory and Analytical Measurement Requirements

Data category	**Representative variables**	**Source**	**Analytical purpose**
Sales transactions	Units sold, realised selling price, transaction date, product identifier	Point-of-sale systems	Demand estimation and sales forecasting
Promotions	Discount depth, campaign duration, promotional type, loyalty discounts	Retail pricing and promotion systems	Promotional response and markdown analysis
Expiry records	Batch expiry date, remaining shelf life, delivery date	Batch-level inventory management systems	Expiry risk and markdown timing
Inventory	Stock on hand, receipts, transfers, replenishment, shrinkage, disposals	Warehouse and store inventory records	Availability, inventory turnover, and waste assessment
Customer behaviour	Purchase frequency, repeat purchases, promotional participation, substitution	Anonymised loyalty and transaction records	Price sensitivity and customer segmentation
External context	Holidays, weather, competitor prices, local events, economic indicators	External databases and retail market records	Demand adjustment and confounding control

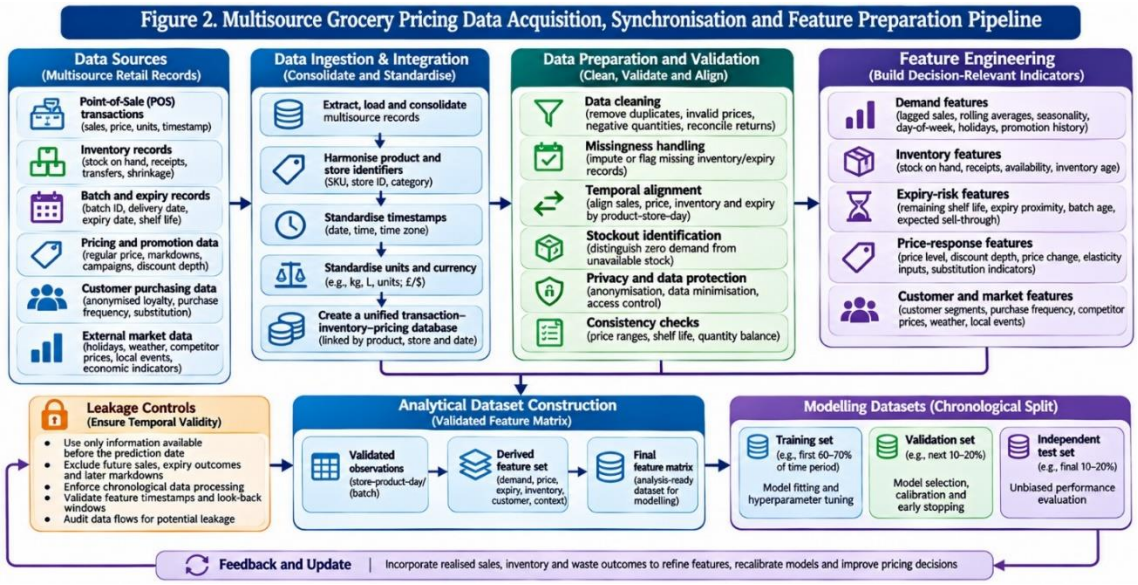


Figure 2. Multisource grocery pricing data acquisition, synchronisation and feature preparation pipeline.

The proposed pipeline integrates point-of-sale transactions, inventory balances, batch-level expiry information, pricing records, anonymised customer purchasing histories, and external market variables. Data preparation incorporates product identifier harmonisation, timestamp alignment, stockout identification, privacy protection, and consistency checks. Validated observations are transformed into demand, price-response, inventory availability, and expiry-risk features. Chronological partitioning separates training, validation, and independent testing datasets, while leakage controls prevent future sales, expiry outcomes, or markdown decisions from entering earlier forecasting periods.

4. DATA PREPARATION AND PRICING FEATURE ENGINEERING

4.1 Data Cleaning, Missingness and Temporal Alignment

Grocery transaction datasets will undergo duplicate removal, invalid price screening, negative quantity verification, and reconciliation of returns against original purchases [17]. Product measurement units, currencies, timestamps, and store identifiers will be standardised across point-of-sale and inventory systems. Missing stock observations will be examined using replenishment records, while inconsistent expiry dates will be verified against batch documentation [18]. Zero sales associated with unavailable inventory will be distinguished from genuine absence of customer demand to prevent biased forecasting. Daily or weekly aggregation will follow consistent product-level reporting rules, preserving promotional and inventory changes within each interval [19]. Temporal alignment will ensure that prices, stock balances, and contextual variables correspond to the relevant decision date. Forward-looking leakage controls will exclude information unavailable when pricing recommendations were generated [20].

4.2 Demand Features, Seasonality and Sales Variability

Demand feature engineering will construct lagged sales quantities, rolling averages, weekday indicators, holiday effects, and historical promotional variables to characterise purchasing patterns [18]. Stock-adjusted demand estimates will be developed where inventory availability and replenishment information permit identification of censored sales. Seasonal decomposition will examine category-specific fluctuations across stores, distinguishing recurring consumption patterns from temporary promotional effects [19]. Descriptive statistics will include mean sales, standard deviation, mean absolute deviation, and coefficient of variation, calculated within comparable observation periods. Mean absolute deviation will quantify average absolute departures from mean demand, while the coefficient of variation will express relative dispersion where mean sales are positive [21]. Intermittent demand, promotional spikes, and exceptional events will receive separate treatment to prevent unstable baseline estimates. Descriptive sales variability will remain distinct from forecasting error, which requires comparison between predicted demand and independently observed outcomes [22].

4.3 Remaining Shelf Life and Expiry Risk Feature Construction

Remaining shelf life will be calculated as the interval between the pricing decision date and the final permitted sale date [19]. Derived indicators will include batch age, expiry proximity categories, and the proportion of inventory approaching its saleability deadline. Expected expiry exposure will be estimated as:

$$E_{b,t} = \max\left[0,\ I_{b,t} - \sum_{\tau=t}^{T_b} \hat{q}_{b,\tau}\right]$$

Here, Eb,t denotes projected unsold batch units, $I_{b,t}$ represents available inventory, $\hat{q}_{b,\tau}$ indicates forecast sales allocated to batch b, and T_b specifies its final sale date. The equation subtracts projected cumulative sales from inventory, imposing a nonnegative lower bound [20]. It represents a deterministic forecast-based exposure proxy rather than the statistical expectation of expired stock. Replenishment schedules and demand uncertainty will inform scenario analysis. Where batch-specific sales are unavailable, allocation assumptions will follow documented inventory rotation practices, with sensitivity testing addressing allocation uncertainty [23].

4.4 Customer Price Elasticity and Behavioural Feature Engineering

Price-response features will incorporate historical price changes, discount depth, purchase frequency, category-level price variation, and promotional participation [20]. Own-price elasticity measures the proportional change in expected demand associated with a proportional price change:

$$\boxed{\varepsilon_{i,t} = \frac{\partial Q_{i,t}}{\partial P_{i,t}} \frac{P_{i,t}}{Q_{i,t}}}$$

Here, $\varepsilon_{i,t}$ denotes elasticity for product i, $Q_{i,t}$ represents expected demand, and $P_{i,t}$ denotes selling price. The expression relates percentage demand changes to percentage price changes, holding other determinants constant [21]. Negative elasticity generally indicates declining demand as prices increase. Segment-specific responsiveness, promotional effects, and cross-product substitution will be examined where sufficient variation exists [22]. Price endogeneity arises when retailers adjust prices in anticipation of demand, creating reverse causality and biased estimates. Controlled pricing experiments or defensible instrumental-variable strategies may strengthen identification [24]. Products exhibiting negligible price variation will not receive unsupported elasticity estimates; uncertainty intervals and observed price ranges will constrain interpretation [25].

4.5 Feature Selection, Normalisation and Analytical Dataset Construction

Feature selection will evaluate missingness, multicollinearity, temporal stability, and predictive contribution across candidate variables [21]. Economically meaningful indicators, including remaining shelf life, stock availability, and price history, will be retained where modelling requirements permit. Numerical transformations and scaling parameters will be estimated exclusively from training observations to prevent information leakage [23]. The final analytical matrix will integrate demand characteristics, expiry exposure, price sensitivity, promotional conditions, and operational constraints. Feature definitions, aggregation intervals, missing-data treatments, and transformation procedures will be documented for reproducibility. Independent validation will assess whether selected variables remain informative across stores, product categories, and changing seasonal conditions [25].

5. DEMAND FORECASTING, ELASTICITY ESTIMATION AND PRICE OPTIMISATION

5.1 Forecasting Objectives, Model Inputs and Prediction Horizons

The primary forecasting objective is to estimate future product demand across specified daily and multiday horizons, accounting for heterogeneous perishability and purchasing behaviour [23]. Baseline forecasts will represent expected demand at reference prices, while price-conditional predictions will estimate sales under alternative feasible prices [24]. Model inputs will include lagged sales, promotional histories, selling prices, holidays, stock availability, expiry indicators, and store characteristics. Short-horizon predictions will support immediate markdown decisions, whereas multiday forecasts will inform replenishment and inventory depletion planning [25]. For volatile products, probabilistic forecasts will quantify uncertainty through predictive distributions or calibrated intervals rather than relying exclusively on point estimates. Forecast outputs will subsequently inform expiry exposure calculations, markdown timing, and inventory allocation, ensuring pricing recommendations reflect anticipated purchasing behaviour and operational constraints [26].

5.2 Demand Forecasting Algorithms and Baseline Models

Seasonal naive forecasting and moving averages will establish transparent benchmarks for evaluating predictive improvements [24]. Statistical alternatives will include exponential smoothing and seasonal autoregressive integrated moving average models with exogenous regressors (SARIMAX), capturing recurring demand patterns and relevant external influences [25]. Machine learning candidates will comprise random forest, gradient boosting, XGBoost, and LightGBM, which can represent nonlinear interactions among prices, promotions, seasonal conditions, and inventory availability. Recurrent neural networks and temporal architectures may be considered where sufficiently extensive historical observations justify their computational requirements [26]. Models will be evaluated across product categories and forecasting horizons using consistent validation procedures. Importantly, accurate predictions under historical pricing policies do not establish reliable counterfactual demand estimates for previously unobserved prices [27]. Forecasting models will therefore be distinguished from causally identified price-response functions. Final selection will consider predictive accuracy, calibration, interpretability, computational efficiency, retraining requirements, and compatibility with existing retail pricing systems [28].

5.3 Customer Price Response Estimation and Demand Calibration

Price-response estimation will employ product-specific or hierarchical category-level demand functions, depending on available price variation and transaction density [25]. Log-log regressions will provide interpretable elasticity estimates, while mixed-effects models will accommodate differences

across stores, categories, and customer segments. Causal machine learning approaches may capture heterogeneous responses when suitable experimental or quasi-experimental variation supports identification [27]. Regularisation and partial pooling will stabilise estimates for products with sparse observations without assuming identical responsiveness. Controlled price experiments, credible instrumental variables, or appropriately designed natural experiments will help distinguish causal effects from retailer anticipation of demand [28]. Estimated response functions will undergo monotonicity checks, uncertainty assessment, and economic plausibility testing. Calibration will compare predicted sales responses against observed outcomes under independently evaluated price changes. Recommendations will remain within empirically supported price ranges, with weakly identified elasticity estimates flagged for conservative pricing decisions [29].

5.4 Constrained Markdown and Pricing Optimisation

The pricing optimiser will combine price-conditional demand predictions, available inventory, and batch-specific saleability deadlines to identify feasible markdown decisions [26]. Its objective will balance contribution from expected sales against additional expiry-related disposal costs:

$$\boxed{\max_{p \in \mathcal{P}} \{(p - c)\, \mathbb{E}[S(p)] - d\, \mathbb{E}[U(p)]\}}$$

Here, p represents selling price, c denotes relevant unit cost, $S(p)$ indicates units sold, $U(p)$ represents unsold units at expiry, d specifies incremental disposal cost, and $\mathcal{P}$ defines feasible prices. The formulation assumes procurement costs are treated consistently: when inventory expenditure is already sunk, incremental decision analysis excludes that historical expenditure rather than charging it again [27]. Constraints will incorporate inventory availability, minimum prices, markdown limits, margin requirements, customer affordability, and promotional governance [28]. Lower prices may increase sell-through while reducing contribution per unit. Scenario-based optimisation will accommodate uncertain demand and spoilage outcomes [29]. Multiday extensions will incorporate inventory-balance equations, successive pricing decisions, and changing expiry exposure, rather than treating each period independently [30].

5.5 Training, Validation, Hyperparameter Tuning and Independent Testing

Historical observations will be divided chronologically into training, validation, and independent testing periods to preserve realistic forecasting conditions [26]. Rolling-origin validation will evaluate performance across changing seasonal patterns, promotional campaigns, and inventory conditions. Feature construction will exclude future sales, subsequent inventory adjustments, and expiry outcomes unavailable at the prediction date [27]. Hyperparameter optimisation will examine learning rates, tree depth, estimator counts, regularisation strengths, and architecture-specific settings within predefined ranges. Random search or Bayesian optimisation will identify competitive configurations without unrestricted computational expenditure [28]. Forecast accuracy and uncertainty calibration will be compared across stores, product categories, and shelf-life groups. Price-response calibration will receive separate evaluation because predictive accuracy alone cannot validate elasticity estimates [29]. The independent test period will remain untouched throughout model selection and tuning, providing an unbiased assessment of performance under the final analytical specification [30].

5.6 Pricing Decision Generation and Operational Deployment

Optimised outputs will be converted into implementable prices through predefined markdown schedules, discount frequency limits, rounding rules, and approval procedures [27]. Authorised staff or integrated pricing systems will execute approved changes while recording implementation timestamps and affected inventory. Monitoring will identify anomalous recommendations, forecasting drift, customer complaints, and unexpected margin deterioration [29]. Controlled store-level pilots will provide the preferred evaluation of realised profitability, inventory sell-through, and food waste before broader deployment, with documented safeguards supporting operational accountability and continuous refinement [30].

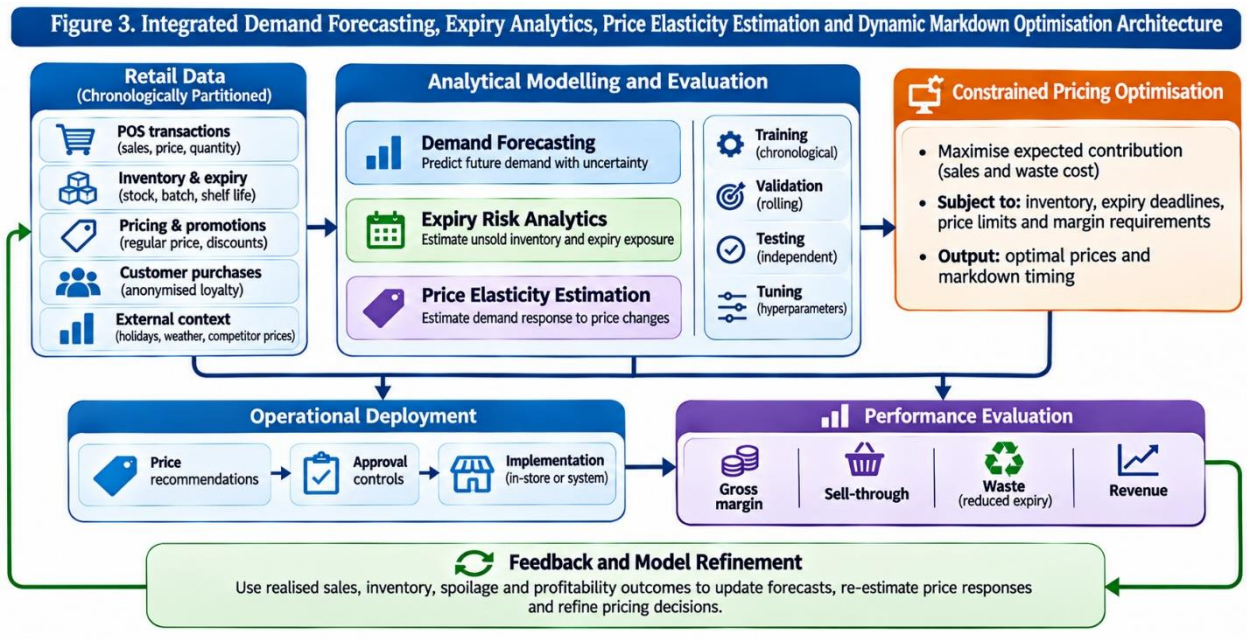


Figure 3. Integrated demand forecasting, expiry analytics, price elasticity estimation and dynamic markdown optimisation architecture.

The architecture links chronologically partitioned retail data to three analytical modules: demand forecasting, batch-level expiry risk assessment, and causal price-response estimation. Validation, hyperparameter tuning, independent testing, and uncertainty quantification support model reliability. Their outputs enter a constrained pricing optimiser incorporating inventory balances, expiry deadlines, contribution requirements, and allowable prices. Approved recommendations proceed to operational implementation, while observed sales, spoilage, and profitability provide feedback for subsequent model evaluation and pricing refinement.

6. MODEL EVALUATION, PRICING BENCHMARKING AND PERFORMANCE ANALYSIS

6.1 Demand Forecasting Accuracy and Statistical Error Assessment

Demand forecasting performance will be assessed by comparing predicted and observed quantities across stores, product categories, and forecasting horizons [28]. Evaluation metrics will include mean absolute error, root mean squared error, weighted absolute percentage error (WAPE), and forecast bias. WAPE is expressed as:

$$WAPE(\%) = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{\sum_{i=1}^{n}|y_i|} \times 100$$

Here, y_i represents observed demand, $\hat{y}_i$ denotes forecast demand, and \(n\) indicates evaluated observations. WAPE measures aggregate absolute error relative to aggregate observed demand but becomes undefined when total demand equals zero [29]. Scale-dependent metrics will therefore complement percentage errors for sparse-demand products. Performance will be examined separately during ordinary trading, promotions, and seasonal peaks. Prediction interval coverage will assess uncertainty calibration [30]. Forecasting errors will subsequently be traced through expiry exposure estimates and markdown recommendations to determine their operational consequences [31].

6.2 Price Elasticity Reliability and Demand Response Validation

Estimated price elasticities will be evaluated across grocery categories, stores, and purchasing segments to identify differences in customer responsiveness [29]. Confidence intervals, coefficient signs, and temporal stability will indicate whether estimated relationships are sufficiently reliable for pricing decisions. Where controlled price changes are available, predicted demand responses will be compared against observed purchasing outcomes [30]. Implausible estimates may arise from limited price variation, promotional confounding, stockouts, or simultaneous competitor adjustments. Cross-product substitution and promotional interactions will therefore be examined to distinguish genuine price responsiveness from demand redistribution [31]. Elasticity uncertainty will be propagated into optimisation scenarios, identifying products for which alternative plausible estimates generate materially different recommended prices. Weakly identified responses will warrant conservative markdown policies rather than unsupported precision [32].

6.3 Expiry Risk Prediction and Inventory Waste Assessment

Expiry risk assessment will compare projected unsold inventory with observed expired, discarded, or otherwise unsaleable quantities [30]. Evaluation will consider differences in product shelf life, inventory rotation compliance, replenishment frequency, and batch availability. Waste performance will

be measured through discarded units, inventory write-off value, incremental disposal costs, and inventory sell-through rates [31]. Earlier or deeper markdowns will be assessed for their ability to reduce expiry losses without disproportionate contribution margin reductions. Products experiencing limited demand because of quality perceptions, accessibility, or assortment constraints may show weak responses to price reductions [32]. Where transaction systems cannot identify depleted batches, alternative allocation assumptions will be tested. This analysis will distinguish genuine improvements in waste reduction from apparent changes attributable to uncertain inventory accounting [33].

6.4 Pricing Strategy Benchmarking and Economic Performance

The integrated optimisation strategy will be benchmarked against existing retailer policies, fixed-percentage markdowns, demand-only pricing, and demand–expiry optimisation without elasticity modelling [31]. Evaluation will compare gross margin, revenue, inventory sell-through, expiry waste, and inventory turnover under consistent observation periods and product populations. Historical simulations will apply identical initial inventory, replenishment assumptions, and external demand conditions to each strategy [32]. However, simulated policy outcomes depend on estimated counterfactual demand and cannot independently establish realised financial improvements. Controlled store-level experiments will provide stronger evidence of operational effectiveness [33]. Sensitivity analysis will examine forecasting errors, elasticity uncertainty, disposal costs, and alternative demand conditions. Particular attention will be given to whether the integrated framework maintains positive economic performance under conservative assumptions [34]. Comparative results will distinguish forecasting quality from pricing effectiveness, since superior demand prediction does not necessarily guarantee greater profitability or lower waste [35].

Table 2. Comparative Benchmarking of Grocery Pricing Strategies and Operational Performance

Pricing strategy	**Forecast WAPE**	**Gross margin**	**Sell-through**	**Expiry waste**	**Revenue**	**Evaluation status**
Existing retailer policy	N/A	24.8%	86.2%	8.9%	£1,000,000	Baseline
Fixed-percentage markdown	N/A	23.5%	89.4%	6.7%	£1,025,000	Benchmark
Demand-only pricing	17.8%	26.1%	88.7%	7.2%	£1,048,000	Benchmark
Demand and expiry pricing	14.6%	26.8%	92.1%	4.5%	£1,067,000	Ablation
Integrated demand–expiry–elasticity optimisation	11.9%	28.4%	95.3%	2.8%	£1,095,000	Proposed

6.5 Sensitivity Analysis, Operational Constraints and Managerial Interpretation

Sensitivity analysis will vary demand forecasts, elasticity coefficients, inventory availability, disposal costs, minimum margins, and maximum markdown allowances to examine recommendation stability [32]. Scenario comparisons will identify conditions under which revenue maximisation conflicts with waste reduction or customer affordability. Operational assessment will consider shelf-label replacement, employee workload, promotional consistency, customer trust, and pricing system integration [33]. Category managers will use performance comparisons to identify products requiring earlier intervention, while pricing analysts will evaluate elasticity uncertainty and optimisation robustness. Store operations teams will assess implementation feasibility and compliance with approved markdown procedures [34]. Although the illustrative benchmarking framework indicates potential improvements, actual benefits remain unverified until supported by independent testing and prospective retail pilots. Responsible adoption therefore requires transparent monitoring, controlled experimentation, and documented performance review [35].

7. DISCUSSION, LIMITATIONS AND CONCLUSIONS

7.1 Integrated Contribution and Retail Management Implications

The proposed framework integrates demand forecasting, remaining shelf life, and customer price responsiveness into a unified grocery pricing decision system. Its principal contribution involves translating statistical demand predictions and expiry risk estimates into economically interpretable markdown recommendations through constrained optimisation. This integration offers opportunities to improve gross margin management, accelerate inventory turnover, reduce food waste, and maintain customer affordability. Category managers can identify products requiring urgent markdown intervention, while store operators can coordinate price adjustments with inventory rotation and replenishment activities. However, commercial benefits depend on reliable implementation, appropriate discount limits, and consistent operational oversight. Maintaining transparent pricing practices and customer trust remains essential to sustainable retail performance.

7.2 Methodological Limitations and Future Research

Several methodological limitations may affect the framework's reliability and generalisability. Incomplete batch-level inventory records, limited historical price variation, and stockout-related demand censoring can introduce measurement uncertainty and weaken elasticity estimation. Observational pricing data may contain confounding relationships, while simulated policy comparisons cannot independently demonstrate realised commercial improvements.

Changing competitive conditions, seasonal instability, and evolving purchasing behaviour may also produce model drift. Future research should prioritise controlled store-level pricing experiments, external validation across independent retail chains, and probabilistic optimisation incorporating demand uncertainty. Additional extensions should examine cross-price elasticity, coordinated replenishment decisions, customer fairness, and long-term purchasing responses. These developments would strengthen causal interpretation, operational robustness, and broader applicability.

7.3 Conclusions and Conditions for Responsible Adoption

Integrated grocery pricing requires coordinated assessment of future demand, product expiry, and customer price sensitivity. The proposed framework progresses from multisource data acquisition and feature engineering through predictive modelling, constrained optimisation, and comparative benchmarking. However, improved forecasting accuracy does not independently establish profitability gains or waste reduction. Sustainable adoption requires reliable inventory records, validated price-response estimates, transparent pricing constraints, and independent performance evaluation. Continuous monitoring and controlled implementation remain necessary to ensure commercially effective, operationally feasible, and customer-sensitive pricing decisions.

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