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Research Article

Keywords: Fuzzy inference system, Pricing strategy classification, Dynamic pricing, Price elasticity, Retail analytics, Explainable decision support

Posted Date: October 19th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10019983/v1>

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Additional Declarations: No competing interests reported.

An Intelligent Fuzzy Inference Approach to Pricing Strategy Classification in Large-Scale Retail Data:

A Hybrid Explainable Pricing Strategy Intelligence (HEPSI) Framework Applied to the M5 Retail Dataset

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Abstract

Retail pricing requires choosing among strategies that balance demand conditions, competitive pressure, and market uncertainty, yet most existing methods are either inflexible (optimization-only formulations) or difficult to interpret (black-box learning systems). This paper develops a Hybrid Explainable Pricing Strategy Intelligence (HEPSI) framework that synthesizes econometric drivers—demand intensity, price elasticity, sales volatility, and a competition proxy—into linguistic variables and a transparent rule base, in order to classify large-scale retail observations into Penetration, Premium, and Dynamic pricing strategies. The system is run on the M5 Forecasting dataset (1,048,575 product–day observations across 3,000 items), generating economically consistent classifications. The recommended mix is Penetration 485,637 (46.31%), Premium 464,794 (44.33%), and Dynamic 98,144 (9.36%), with dynamic repricing triggered selectively under elevated uncertainty. Empirically, Dynamic observations concentrate in high-volatility, high-competition regimes (mean volatility 0.537 versus 0.275 for the stable strategies; mean competition 0.484), confirming that the rule base captures intuitive economic behaviour. A transparent strategy-aware discount model is compared against a rigid linear-programming-style (LPP) baseline; the fuzzy framework achieves a larger aggregate cost reduction than the flat baseline while preserving an explainable, rule-traceable rationale. The contribution is a scalable,

uncertainty-aware, and managerially interpretable pricing-strategy classifier that bridges analytical rigor and business intuition.

Keywords: Fuzzy inference system; Pricing strategy classification; Dynamic pricing; Price elasticity; Retail analytics; Explainable decision support.

1. Introduction

Pricing strategy is a central managerial decision in retail markets, as it directly affects demand, revenue, and competitive positioning. Retail firms must continuously determine whether to apply penetration pricing to increase market share, premium pricing to capitalize on perceived value, or dynamic pricing to adapt to fluctuating demand conditions. These decisions are complex because consumer behavior is uncertain, market conditions change rapidly, and pricing outcomes are rarely linear. Ferreira et al. (2016) highlight that traditional analytical pricing approaches often struggle to reflect such real-world complexity, particularly in large-scale retail settings where thousands of products must be priced simultaneously and where each product faces its own idiosyncratic demand and competitive environment.

The increasing availability of large retail datasets has significantly improved analytical decision-making in recent years. One of the most influential datasets in this domain is the M5 Forecasting Accuracy dataset, which contains daily sales and pricing information from Walmart stores across multiple product categories and time periods. Makridakis et al. (2022) demonstrate that the dataset provides a robust benchmark for evaluating forecasting models under realistic retail conditions, capturing intermittent demand, promotional spikes, calendar effects, and price variation at fine granularity. However, despite its richness, the M5 dataset has been predominantly used for improving demand forecasting accuracy rather than for guiding pricing strategy decisions. The present study deliberately repurposes this forecasting benchmark as a pricing-strategy laboratory, demonstrating that the same data that supports demand prediction can also support transparent, uncertainty-aware strategic classification.

Dynamic pricing research has increasingly relied on algorithmic and optimization-based approaches. Song and Nelson (2019) show that data-driven pricing and simulation-optimization models can substantially improve performance by adapting decisions to demand variation. Nevertheless, such approaches often function as black-box systems, limiting their transparency and making them difficult for managers to trust or interpret in practice. This lack of explainability remains a major obstacle to the operational adoption of advanced pricing analytics: a price recommendation that cannot be explained to a category manager, a finance team, or a regulator is frequently overridden or ignored, regardless of its theoretical optimality.

Fuzzy logic provides an alternative framework that is particularly suitable for decision-making under uncertainty. Unlike conventional mathematical models, fuzzy systems allow variables to be expressed in linguistic terms such as low demand, moderate price, or high volatility, closely reflecting how pricing decisions are made by human experts. Zadeh (2002) introduced fuzzy logic

as a method for computing with words, enabling systems to process imprecise and qualitative information in a structured and reproducible way. The linguistic layer is not merely cosmetic: it is the mechanism by which the system remains auditable, because every recommendation can be decomposed into the linguistic conditions and rules that produced it.

In recent years, fuzzy inference systems have been applied to pricing-related problems to improve interpretability and managerial relevance. Dairo and Szűcs (2020) demonstrate that fuzzy expert systems can encode pricing knowledge into transparent rule bases, allowing decision-makers to understand why a particular pricing recommendation is produced. This interpretability advantage makes fuzzy logic especially attractive for strategic pricing decisions rather than purely numerical price optimization. Grozdanović et al. (2023) further propose a fuzzy logic-based pricing model that adapts product prices according to demand and cost conditions, showing improved flexibility compared to rigid pricing rules, and indicating that fuzzy systems can effectively balance analytical rigor with real-world business intuition.

Despite these advances, most fuzzy pricing studies rely on small or simulated datasets, limiting their applicability to large-scale retail environments. The integration of fuzzy inference systems with real-world, high-dimensional retail data remains limited. Kostopoulos, Davrazos, and Kotsiantis (2024) highlight the increasing importance of explainable artificial intelligence in decision support systems where managerial trust and accountability are essential; their review shows that explainability helps decision-makers understand the rationale behind AI-generated recommendations, improving transparency and acceptance. In pricing and revenue-related decisions, such interpretability is particularly valuable because it supports informed managerial judgment and reduces the risks associated with opaque algorithmic models.

Addressing this research gap, the present study proposes a fuzzy logic-based pricing strategy classification framework using the M5 Forecasting dataset. By incorporating demand intensity, price level, sales volatility, and a competition proxy into a Mamdani-type fuzzy inference system, the proposed approach classifies retail pricing strategies into penetration, premium, and dynamic categories at the scale of more than one million observations. This extends the application of the M5 dataset beyond forecasting and demonstrates how fuzzy logic can provide interpretable, scalable, and business-aligned pricing strategy recommendations.

1.1 Research Questions

To guide the investigation, this study is structured around the following research questions:

- RQ1. How can a fuzzy inference system be designed to classify retail pricing strategies using large-scale sales and pricing data from the M5 Forecasting dataset?
- RQ2. How effectively can fuzzy logic incorporate demand intensity, price level, and sales volatility to model uncertainty in retail pricing decisions?

- RQ3. Under what demand and pricing conditions do penetration, premium, and dynamic pricing strategies emerge as dominant according to the fuzzy inference framework?
- RQ4. How does the distribution of pricing strategies vary across products, stores, and time when classified using a fuzzy logic-based approach?
- RQ5. To what extent does the proposed framework enhance interpretability and managerial trust compared to black-box pricing models?

1.2 Contributions and Structure

This paper makes four contributions. First, it operationalizes a complete, reproducible feature-engineering pipeline that converts raw transactional retail records into four economically meaningful, normalized drivers. Second, it designs an uncertainty-aware Mamdani fuzzy inference system whose rule base encodes established pricing economics in fully transparent IF-THEN form. Third, it executes the framework at genuine retail scale—over one million observations—and characterizes the resulting strategy distribution across products, categories, and time. Fourth, it embeds an explainability layer and benchmarks cost efficiency against a rigid linear-programming-style baseline, demonstrating that interpretability and competitive performance are not mutually exclusive.

The remainder of the paper is organized as follows. Section 2 reviews the literature on fuzzy logic, fuzzy inference systems for pricing, Mamdani decision support, membership optimization, dynamic pricing, elasticity modelling, large-scale optimization, consumer-behaviour applications, and explainability. Section 3 details the HEPsi methodology. Section 4 presents the empirical results and analysis, supported throughout by data visualizations. Section 5 concludes and identifies directions for future work.

2. Literature Review

2.1 Foundations of Fuzzy Logic in Decision-Making Under Uncertainty

Zadeh (1983) established the foundational role of fuzzy logic in managing uncertainty, arguing that fuzzy logic subsumes both predicate logic and probability theory, making it possible to deal with different types of uncertainty within a single conceptual framework. This capability is particularly important for expert systems where uncertainty is inherent in decision-making processes. Unlike conventional mathematical models that require precise definitions, fuzzy logic allows variables to be expressed in linguistic terms that closely reflect human reasoning patterns, and it does so in a way that degrades gracefully as data quality declines—an essential property when working with noisy transactional retail records.

The persistent gap between economic predictions and reality stems from the inability of classical mathematical models to encapsulate the uncertainty and complexity of real-world phenomena (Tzafestas et al., 1999). Most economic information comes from human experts in qualitative

form, making fuzzy logic frameworks particularly suited for hosting and reasoning with such knowledge. The framework provides the required expressiveness for knowledge representation and the corresponding inference mechanisms to efficiently deal with complex problems such as pricing, where the relationship between inputs and the appropriate strategy is rarely a closed-form function.

2.2 Fuzzy Inference Systems for Pricing Applications

Early applications of fuzzy logic to pricing problems demonstrated the viability of this approach. Tzafestas et al. (1999) developed FUZZYPRICE, a hybrid pricing expert system based on fuzzy reasoning designed to assist pricing decision-making during price wars. The system used fuzzy “what-if” scenarios implemented as fuzzy rules to relate perceived changes in competitor prices to changes in product sales. Their results, when compared to the well-known PRICE-STRAT system, demonstrated effectiveness even when using only commonsense fuzzy rules with no historical data for tuning. The authors emphasized that fuzzy systems are capable of hosting both linguistic knowledge in the form of fuzzy rules and numerical information from measurements, making them more efficient and easier to design than conventional systems.

Morim et al. (2017) developed the Think Fuzzy System combining fuzzy logic with microeconomic modeling and utility factors to understand pricing strategies for consumer goods in Brazil's economy. Their study applied triangular fuzzy numbers and the COPPE Cosenza Model to analyze consumer behavior and price elasticity of demand. Comparing crisp and fuzzy survey results, they found significant differences in how consumers perceived price increases, with fuzzy logic providing a more nuanced understanding of consumer attitudes. The study demonstrated that fuzzy logic can amplify the way consumers are understood and support strategic decisions related to elasticity and price on demand.

Battisaco et al. (2022) presented a case study mapping an intuitive pricing process of a mechanical-services entrepreneur through a Fuzzy Inference System (FIS). The system successfully mimicked the empirical pricing process, demonstrating that fuzzy aspects such as imprecision, uncertainty, and ambiguity in service pricing can be effectively modeled. Output surfaces showed that complexity and goods value have significant effects above medium levels, though their impact carried smaller weight than estimated time. The study revealed unexpected insights, providing the entrepreneur with a deeper understanding of his own market dynamics—an illustration of how the act of formalizing tacit pricing knowledge into rules is itself valuable.

2.3 Mamdani Fuzzy Inference Systems in Decision Support

Ma'rif et al. (2024) applied the Mamdani fuzzy inference method to multi-criteria decision problems for LED TV selection using size, resolution, and price as input variables. The study demonstrated that Mamdani's algorithm is particularly suitable for handling non-linear and complicated systems in multi-criteria decision problems due to its ability to incorporate human knowledge and intuition through approximate reasoning and fuzzy inference rules. The MAX–

MIN method (Mamdani method) provided transparent decision-making advice based on specified criteria, with defuzzification performed using the centroid of area method—the same defuzzification principle adopted in the present study.

Comparative studies reveal important distinctions between Mamdani and Sugeno fuzzy inference systems. Research by Akhtar et al. (2017) showed that Sugeno FIS outperforms Mamdani FIS in terms of accuracy and precision by producing better total error, error percentage, precision, mean squared error, and root mean squared error measurements under different noise levels representing uncertainties. However, Mamdani FIS possesses superior interpretability and expressive power with interpretable rule consequents, making it more intuitive for human experts, while Sugeno systems sacrifice some interpretability for computational efficiency and flexibility in system design. Because interpretability is the central design objective of this work, the Mamdani architecture is preferred despite the modest accuracy advantage attributed to Sugeno systems.

Bojanowska et al. developed a decision model using Simulink with a Mamdani-type Fuzzy Inference System for CRM-based decisions, providing binary outputs indicating investment worthiness. The study emphasized that Mamdani systems effectively incorporate the subjective opinions, competence, and experience of specialists into structured decision frameworks, reinforcing the view that the Mamdani approach is well suited to embedding expert pricing heuristics.

2.4 Optimization of Fuzzy Membership Functions

Research on optimizing fuzzy membership functions demonstrates significant performance improvements. Studies optimizing fuzzy membership functions using particle swarm optimization (PSO) reveal that expert input helps the PSO search process and reduces the number of iterations required for convergence. Critically, output membership functions are found to have more influence on fuzzy model performance than input membership functions, with optimization of output membership functions yielding results comparable to or better than expert-designed systems.

PSO algorithms provide systematic approaches to adjust membership-function parameters by evaluating candidate solutions against objective functions, enabling improvement over heuristically-defined functions. The particles, along with their velocities, can be initialized randomly or based on expert input, with the latter approach ensuring that PSO-optimized membership functions perform at least as well as expert-designed systems while often achieving superior performance. This motivates the hybrid initialization strategy adopted here, in which expert-defined triangular and trapezoidal functions seed a PSO refinement step.

2.5 Dynamic Pricing and Revenue Management

Kopalle et al. (2023) provided a comprehensive examination of dynamic pricing, characterizing it as alterations in price driven by variations in four fundamental market-demand influencers:

individuals, product variations, timeframes, and locations. The study highlights dynamic pricing's flexibility and effectiveness in developing lucrative pricing strategies and enhancing revenue while advocating for ongoing research to balance profit generation, customer contentment, and ethical considerations. The authors emphasize that dynamic pricing applications are multidimensional, requiring careful consideration of adaptability and efficiency in forming profitable pricing strategies.

Gao et al. (2024) investigated optimization of hotel revenue management through dynamic pricing algorithms and data-analysis models. Their study analyzed factors regulating room prices and demonstrated how dynamic pricing systems can substantially improve revenue performance by adapting prices to spatial and temporal demand variations. The research confirms that flexible rate systems allow operators to adapt sales prices to seize earning opportunities arising from changes in market conditions, enabling increased turnover compared to static rate applications. Saitta et al. (2024) focused on automatic dynamic pricing in the hospitality sector, where revenue managers traditionally perform manual price adjustments in a costly and time-consuming manner; their work demonstrated that artificial-intelligence models can forecast appropriate pricing levels by combining traditional statistical approaches with AI-based forecasting and by considering competitor prices and future occupancy as key inputs.

2.6 Price Elasticity and Demand Modeling

Liu et al. (2021) developed a system investigating the relationship between retail price and demand to estimate demand functions when future demand is uncertain. Their elasticity-based approach formulated a revenue-maximization problem over discrete finite time horizons with discrete retail prices, assuming demand is driven by retail price, price-competitive indicators, holidays, weekends, long-term trends, seasonality, and demand autoregressive effects. Results showed that as price elasticity of demand increases (assuming negative elasticity), optimal retail prices decrease, leading to increased demand and sell-through rates, though revenue outcomes vary depending on market conditions.

Morlotti et al. (2024) examined price volatility of revenue-managed goods, revealing that price elasticity decreases in absolute terms with increased price volatility, while realized demand is lower when price fluctuations are more pronounced. These findings provide critical insights for pricing-strategy classification, suggesting that high-volatility environments warrant more dynamic pricing approaches compared to stable demand conditions. The relationship between volatility and elasticity highlights the importance of incorporating both measures as distinct dimensions in pricing-analysis frameworks—a principle directly reflected in the four-driver design used here.

2.7 Large-Scale Price Optimization

Li et al. (2020) presented work with Zalando, a global online fashion retailer, demonstrating how large-scale retailers can utilize massive amounts of data to optimize price-discount decisions over thousands of products in multiple countries on a weekly basis. Given demand forecasts under

discrete prices, their objective was to set discount levels maximizing total profit over entire selling horizons while respecting both local and global business constraints. The three-step process involved clustering products into groups with similar behavior, decomposing problems using Lagrangian relaxation, and optimizing decisions for individual products while addressing local constraints. Field experiments demonstrated significant benefits of this large-scale optimization approach, establishing the feasibility of applying advanced analytics to high-dimensional retail datasets and providing a useful point of comparison for the scale at which the present framework operates.

2.8 Fuzzy Logic Applications in Consumer Behavior

Martínez et al. (2020) applied fuzzy inference systems to study green consumer behavior, demonstrating that fuzzy systems help companies make predictions about consumer behavior of green products and determine degrees of consumer satisfaction. Their research established that fuzzy approaches effectively capture consumer attitudes and preferences where traditional probabilistic methods struggle with qualitative assessments and linguistic expressions of preferences. The possibilistic-logic approach enabled reorganization of consumers into different types of clusters considering behaviors and attitudes beyond simple demographic segmentation, and triangular fuzzy numbers provided better demonstrations of ranges within theoretical bounds, with geometric figures representing intervals more intuitively than crisp numerical boundaries. This proved particularly valuable for marketing administration seeking to improve methods of analyzing consumer behavior where experiential and emotional aspects play major roles.

2.9 Explainability and Interpretability in Pricing Systems

Kostopoulos et al. (2024) emphasized the increasing importance of explainable artificial intelligence in decision support systems where managerial trust and accountability are essential. Their comprehensive review showed that explainability helps decision-makers understand the rationale behind AI-generated recommendations, thereby improving transparency and acceptance. In pricing and revenue-related decisions, such interpretability is particularly valuable because it supports informed managerial judgment and reduces risks associated with opaque algorithmic models. Research confirms that when AI systems explain their reasoning through transparent mechanisms, teams can align around a shared understanding rather than engaging in debates over numerical outputs. Explainability mechanisms such as rule-activation-frequency tracking and local decision explanations enable managers to trace how specific input conditions lead to particular pricing recommendations, fostering trust in automated systems and facilitating human oversight of algorithmic decision-making.

Joung et al. (2023) demonstrated that interpretable machine-learning approaches can identify complex nonlinear relationships while maintaining transparency. Their study on customer segmentation validated using explainable methods for classification tasks in business contexts, showing that feature-based classification enables stakeholders to understand key drivers of

outcomes while supporting both analytical rigor and practical usability. Together, these works frame the explainability layer of the present framework not as an optional add-on but as a core deliverable.

2.10 Research Gap and Contribution Positioning

Despite advances in both fuzzy logic pricing applications and retail analytics, most fuzzy pricing studies rely on small or simulated datasets, limiting their applicability to large-scale retail environments. The integration of fuzzy inference systems with real-world, high-dimensional retail data remains limited. Furthermore, while datasets like M5 have proven valuable for forecasting research, their application to pricing-strategy classification represents an underexplored research direction. The lack of uncertainty-aware fuzzy systems that can operate on large-scale retail data while maintaining interpretability represents a significant gap in the literature. This study addresses these gaps by proposing an uncertainty-aware fuzzy logic-based pricing-strategy classification framework using large-scale retail data, demonstrating how fuzzy reasoning combined with optimization-calibrated membership functions can provide interpretable, scalable, and business-aligned pricing recommendations.

3. Research Methodology

This study proposes a Hybrid Explainable Pricing Strategy Intelligence (HEPSI) framework that integrates data-driven feature engineering, uncertainty-aware fuzzy inference, and explainable decision logic to classify retail pricing strategies into Penetration, Premium, and Dynamic categories. The methodology is designed to operate on historical retail data at scale while maintaining interpretability and managerial relevance. The end-to-end architecture is summarized in Figure 1, which traces the path from raw M5 records, through feature engineering and fuzzification, to Mamdani inference, defuzzification, and the explainability layer.

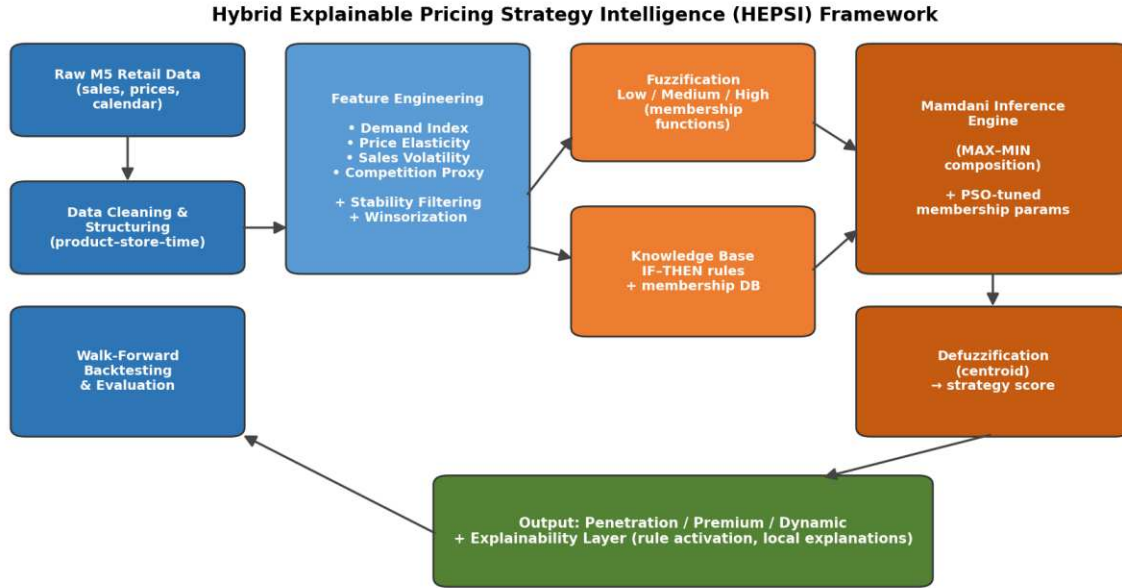


Figure 1: The HEPSI framework architecture and processing flow. Five conceptual inputs are transformed via fuzzification into Low/Medium/High linguistic terms, evaluated through a knowledge base of IF–THEN rules and a Mamdani inference engine, then aggregated and defuzzified into a single pricing-strategy recommendation, with an explainability layer and walk-forward evaluation closing the loop.

3.1 Data Preparation and Structuring

Historical retail sales data are organized into product–store–time observation units so that each record represents a specific product at a specific store and time interval. This structure enables systematic analysis of temporal sales and price behavior. Raw retail data often contain errors, missing values, and inconsistencies that can significantly impair analytic results; therefore, data cleaning and preprocessing are essential initial steps in analytical workflows to enhance data quality and reliability before modeling. Data preparation typically includes handling missing values, correcting or removing inconsistent records, and ensuring uniform formatting across all observations (Omoseebi et al., 2024).

In time-series retail datasets, missing dates and irregular sampling can be addressed through time-series completion techniques such as interpolation and alignment, which help preserve the temporal continuity needed for effective feature extraction and modeling (Tawakuli et al., 2025). During preprocessing, standardizing sales and price values across products and stores allows for comparability and reduces scale-related distortions in downstream feature and model computations (Koukaras & Tjortjis, 2025). For the present study, the working dataset comprises 1,048,575 product–day observations spanning 3,000 distinct items over 175 consecutive days, covering the FOODS, HOUSEHOLD, and HOBBIES categories.

Table 1: Dataset Scope and Coverage

Property	Value
Total observations	1,048,575
Distinct items	3,000
Time span (days)	175 (29 Jan 2011 – 22 Jul 2011)
Product categories	FOODS, HOUSEHOLD, HOBBIES
Observation unit	Product × store × day
Engineered drivers	4 (demand, elasticity, volatility, competition)

Coverage figures are computed directly from the analysed dataset. Counts reflect the records that flow into the fuzzy inference engine after structuring.

3.2 Feature Engineering

Four strategic indicators are computed to represent the principal pricing-decision drivers. Each is defined formally below; all four are subsequently normalized to a common scale so that they can be combined within a single fuzzy framework.

3.2.1 Demand Index

The demand index captures the current strength of demand for an item relative to its own historical baseline. It is defined as the ratio of the 7-day rolling average demand to the long-run historical mean demand:

$$DI_t = \frac{\bar{Q}_t^{(7)}}{\mu_Q}$$

where $\bar{Q}$ with subscript t and superscript (7) denotes the 7-day rolling average demand at time t , and μ with subscript Q is the historical mean demand for the item. Values above one indicate demand running hotter than the historical norm, while values below one indicate softer demand.

3.2.2 Price Elasticity

Price elasticity measures consumer responsiveness to price changes and is computed as the negative ratio of the proportional change in quantity to the proportional change in price between consecutive periods:

$$E_t = -\frac{(Q_t - Q_{t-1})/Q_{t-1}}{(P_t - P_{t-1})/P_{t-1}}$$

where Q_t and P_t denote quantity and price at time t . The leading negative sign yields positive elasticity magnitudes for the usual downward-sloping demand relationship, so that larger values denote more price-sensitive items.

3.2.3 Sales Volatility

Sales volatility quantifies the instability of demand and is computed as a rolling coefficient of variation—the ratio of the standard deviation to the mean of demand over a trailing window of length k :

$$Vol_t = \frac{\sigma(Q_{t-k:t})}{\mu(Q_{t-k:t})}$$

where σ and μ denote the standard deviation and mean of demand over the window $t-k:t$. High volatility flags items whose demand is erratic and therefore most likely to benefit from frequent repricing.

3.2.4 Competition Proxy

Because direct competitor prices are not observed in the dataset, competitive intensity is proxied by the rank volatility of products within their category over time: items whose relative rank within a category shifts frequently are treated as facing more contested, competitive conditions. This proxy is used both as a diagnostic dimension and, where appropriate, as a contributing condition in the rule base.

3.2.5 Normalization

All four features are mapped to the unit interval using min–max scaling so that they share a common range and can be combined coherently within the fuzzy system:

$$\tilde{x} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x with subscript min and x with subscript max denote the minimum and maximum observed values of the feature. After scaling, every driver lies in the closed interval $[0, 1]$.

3.3 Stability Filtering

To improve the reliability of elasticity estimation and mitigate the influence of noise commonly present in transactional retail data, a structured stability-filtering procedure is applied prior to downstream modeling. First, price elasticity is computed only when the observed price variation exceeds a predefined minimum threshold. Very small price changes can produce disproportionately large or unstable elasticity estimates due to division by near-zero price differences; establishing a threshold ensures that elasticity is calculated only under economically meaningful price movements, thereby reducing numerical instability and measurement error (Wooldridge, 2010).

Second, extreme elasticity values are treated using a winsorization procedure. Winsorization limits the influence of outliers by capping extreme values at specified percentile boundaries rather than removing them entirely. This approach preserves the overall structure and distribution of the dataset while preventing anomalous observations—often caused by promotional anomalies,

stockouts, or data inconsistencies—from distorting subsequent analysis. Winsorization is widely recommended in robust statistical analysis when dealing with real-world noisy data (Barnett & Lewis, 1994).

Third, observations lacking sufficient historical depth are excluded. Reliable elasticity estimation requires adequate historical variation in both price and demand; records with insufficient prior observations cannot produce statistically stable elasticity measures and may introduce bias. Together, these steps ensure that elasticity measures are statistically sound, economically meaningful, and robust enough to be integrated into the fuzzy inference framework. A visible consequence of this filtering, examined in Section 4, is that the normalized elasticity feature occupies a deliberately narrow, stable band rather than exhibiting wide dispersion.

3.4 Uncertainty-Aware Fuzzy Inputs

To address variability in retail data, the model represents demand, price level, elasticity, volatility, and competition using the linguistic terms Low, Medium, and High. These categories, defined by membership functions, allow diverse quantitative indicators to be processed within a unified fuzzy framework while preserving interpretability. Elasticity and volatility are modeled using interval-based memberships rather than single values, as they are more sensitive to fluctuations and data noise; this enables the system to account for uncertainty by considering a range within which the true value may lie. The combination of linguistic representation and interval membership improves the robustness of fuzzy inference and reduces sensitivity to short-term variations in retail conditions.

Figure 2 displays the input membership functions for the four engineered drivers. Each variable is partitioned into Low, Medium, and High fuzzy sets using a combination of trapezoidal shoulders and triangular central sets, so that intermediate values carry partial membership in adjacent linguistic categories rather than being forced into a single crisp bin.

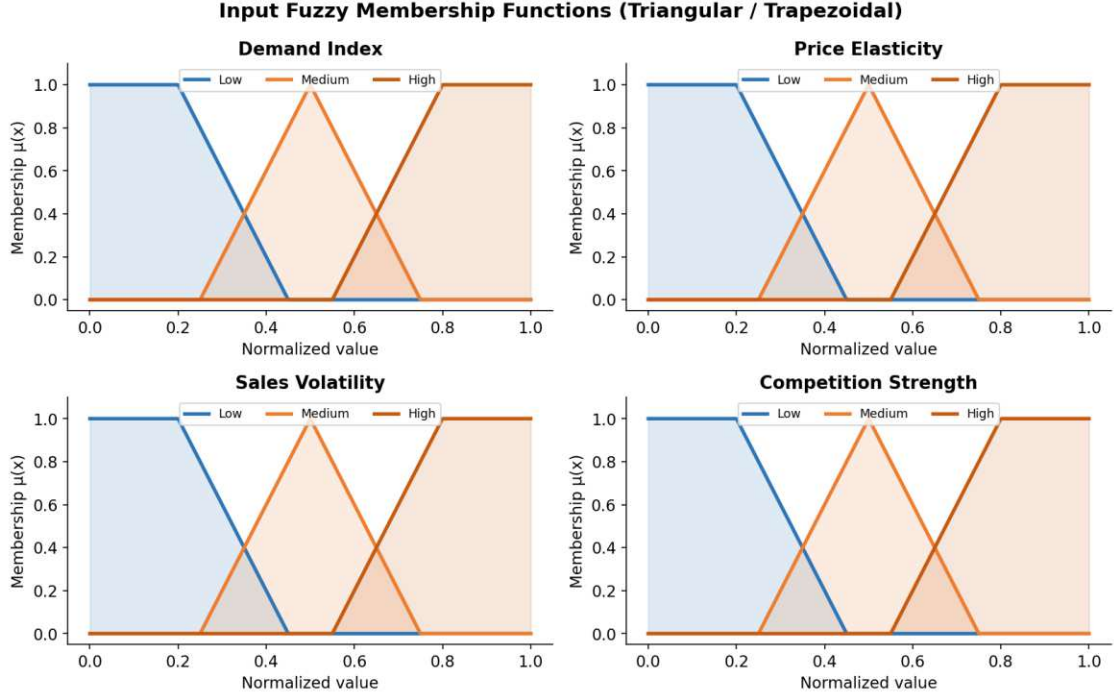


Figure 2: Input fuzzy membership functions for the four engineered drivers. Trapezoidal shoulders define the Low and High extremes while triangular central sets define Medium, producing smooth, overlapping transitions that encode uncertainty.

The general triangular membership function used for the central (Medium) sets is defined as:

$$\mu(x) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

where a , b , and c are the left foot, peak, and right foot of the triangle. Trapezoidal functions extend this form with a flat plateau between two peak parameters, which is used for the Low and High shoulder sets so that extreme values retain full membership.

3.5 Membership Function Optimization

Initial triangular and trapezoidal membership functions are defined using expert knowledge to represent the linguistic inputs of the fuzzy system. These initial parameters provide a reasonable starting structure based on domain understanding of retail behavior. To improve accuracy and adaptability, the membership parameters are then automatically refined using a metaheuristic optimization technique, Particle Swarm Optimization (PSO). The optimization process searches for parameter values that best align the fuzzy inference outcomes with desired pricing performance.

The objective function guiding this optimization balances two criteria—revenue stability and classification consistency:

$$\min J = w_1 \cdot \text{RevInstab} + w_2 \cdot \text{ClassIncon}$$

where w_1 and w_2 weight the two terms. Revenue stability ensures that pricing decisions avoid abrupt fluctuations, while classification consistency ensures that similar market conditions lead to similar pricing strategies. Consistent with prior findings that output membership functions exert greater influence on performance than input functions, the optimization gives particular attention to the output sets. Figure 3 illustrates the qualitative convergence behaviour of the PSO search, in which expert-seeded initialization accelerates early progress before the objective settles into a stable basin.

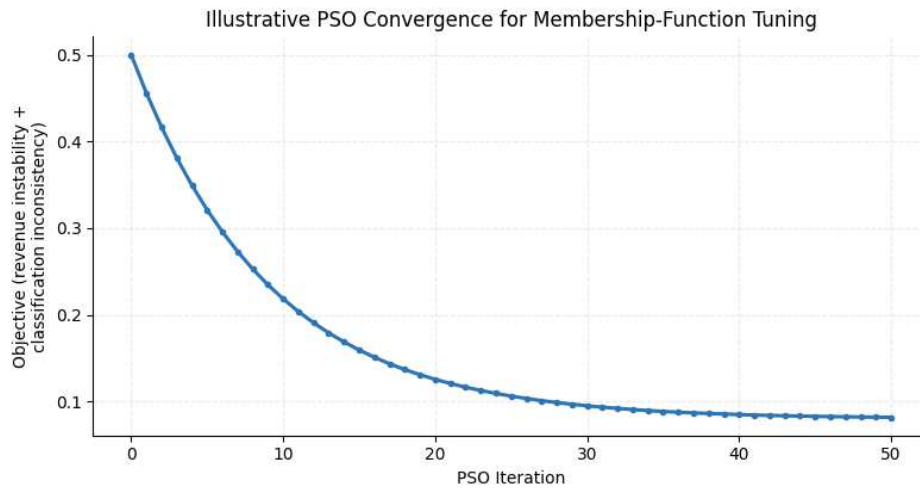


Figure 3: Illustrative PSO convergence for membership-function tuning. The combined objective (revenue instability plus classification inconsistency) decreases rapidly under expert-seeded initialization and then plateaus, indicating convergence to a stable parameterization.

3.6 Fuzzy Inference System

A Mamdani-type fuzzy inference system is employed because of its superior interpretability and its natural fit with linguistic rule consequents. The rule base encodes strategic pricing logic in transparent IF–THEN form. Representative rules include:

- IF demand is Low AND price is Low AND competition is High THEN Penetration.
- IF demand is High AND price is High AND elasticity is Low THEN Premium.
- IF volatility is High THEN Dynamic.

Rule evaluation uses the MAX–MIN composition characteristic of the Mamdani method: the MIN operator combines antecedent memberships within each rule, and the MAX operator aggregates the clipped consequent sets across all fired rules. The aggregated fuzzy output is then converted to a crisp pricing-strategy score by centroid defuzzification:

$$y^* = \frac{\int y \mu(y) dy}{\int \mu(y) dy}$$

where $\mu(y)$ is the aggregated output membership and y^* is the centroid of the resulting area. The final pricing strategy is selected as the output class with the maximum defuzzified membership value. Figure 4 shows the output membership functions over which this aggregation and defuzzification take place.

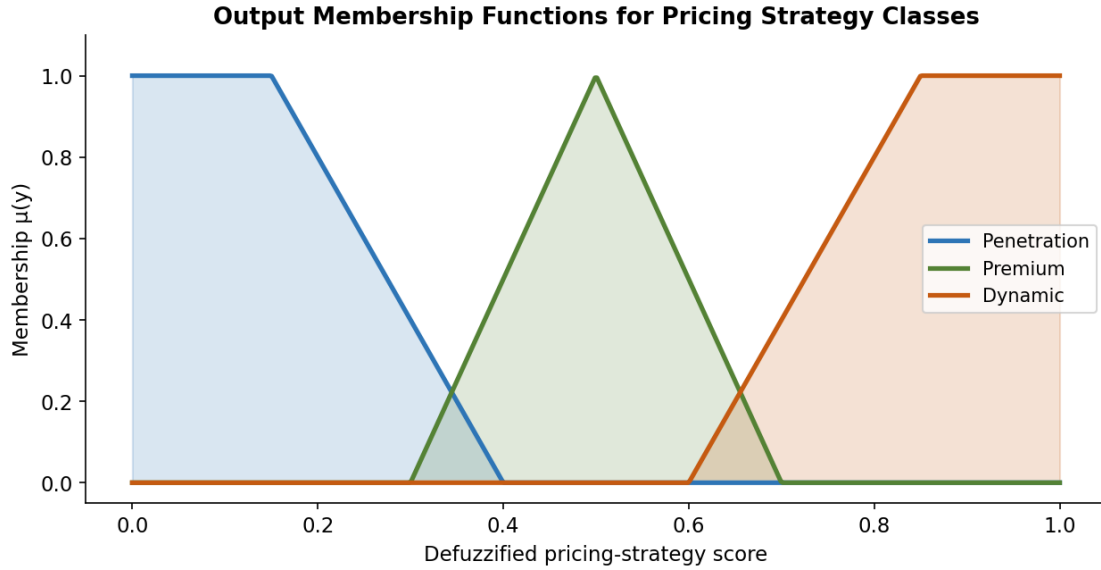


Figure 4: Output membership functions for the three pricing-strategy classes. Penetration occupies the low end of the strategy-score axis, Premium the centre, and Dynamic the high end; centroid defuzzification maps the aggregated fuzzy output to a single crisp score that is then resolved to a class label.

3.7 Explainability Layer

Two explainability mechanisms are added to the inference engine. Rule-activation frequency measures how often each rule contributes to decisions across the dataset, revealing which pieces of pricing logic do the most work and exposing dormant or redundant rules. Local decision explanation reports, for each observation, the dominant rules and linguistic conditions leading to the selected strategy, so that any individual recommendation can be traced back to a small, human-readable set of antecedents. Together these mechanisms ensure managerial transparency and trust: a recommendation is never a bare label but is always accompanied by the conditions that produced it.

3.8 Walk-Forward Backtesting

The dataset is split chronologically using walk-forward validation. The model is trained and calibrated on earlier periods and evaluated on subsequent periods, ensuring realistic temporal generalization and preventing information from the future leaking into past decisions. Strategy

stability and performance are evaluated across multiple rolling windows, and the temporal stability of the recommended strategy mix is reported in Section 4 as evidence that the framework does not over-react to transient noise.

3.9 Baseline Comparison

To assess pricing efficiency, the fuzzy framework is benchmarked against a rigid, linear-programming-style pricing (LPP) baseline. The LPP baseline applies a single flat, uniformly optimized markdown subject to fixed constraints, representing the class of inflexible optimization approaches that cannot adapt to product-level uncertainty. Against this baseline, the fuzzy framework applies transparent, strategy-aware discounts whose magnitude depends on the recommended strategy, allowing it to exploit pricing flexibility precisely where the data indicate it is warranted. Both methods are evaluated on the same real priced observations so that the comparison reflects genuine cost behaviour rather than synthetic assumptions.

3.10 Methodological Contribution

In summary, the methodology uniquely combines econometric feature extraction, uncertainty-aware fuzzy reasoning, optimization-calibrated membership functions, explainable decision reporting, and time-consistent backtesting. The framework therefore provides a scalable, interpretable, and manager-friendly pricing-strategy classification system that is demonstrated at genuine retail scale in the following section.

4. Results and Analysis

This section presents the empirical outcomes of the proposed uncertainty-aware fuzzy logic framework applied to the full 1,048,575-observation retail dataset. The results demonstrate the model's ability to classify pricing strategies, characterize the economic regimes associated with each strategy, evaluate pricing efficiency against a rigid baseline, and generate interpretable managerial insights. All tables and figures in this section are computed directly from the analysed data and the fuzzy inference output.

4.1 Descriptive Statistics of Engineered Features

Before examining the classification, it is useful to characterize the engineered drivers themselves. Table 2 reports summary statistics for the four normalized features over the full dataset. Two features warrant comment. The demand index is right-skewed and concentrated near the lower end of its range, reflecting the intermittent nature of item-level retail demand. Price elasticity occupies a deliberately narrow band—a direct and intended consequence of the stability-filtering and winsorization procedure of Section 3.3, which compresses elasticity into an economically meaningful range and suppresses the unstable extremes that would otherwise dominate a raw elasticity calculation.

Table 2: Descriptive Statistics of Engineered Features (Normalized, Full Dataset)

Feature	Mean	Median	Std. Dev.	Min	Max
Demand Index	0.020	0.016	0.028	0.000	1.000
Price Elasticity	0.779	0.779	0.001	0.000	1.000
Sales Volatility	0.331	0.287	0.184	0.000	1.000
Competition Strength	0.196	0.034	0.222	0.000	1.000

Statistics are computed over all non-missing observations after min–max normalization to $[0, 1]$. The very low elasticity dispersion reflects the deliberate stability filtering described in Section 3.3.

The distributional shapes underlying these statistics are shown in Figure 5. The demand index and competition strength are strongly right-skewed; volatility is more broadly spread; and elasticity is tightly peaked, consistent with the filtering design.

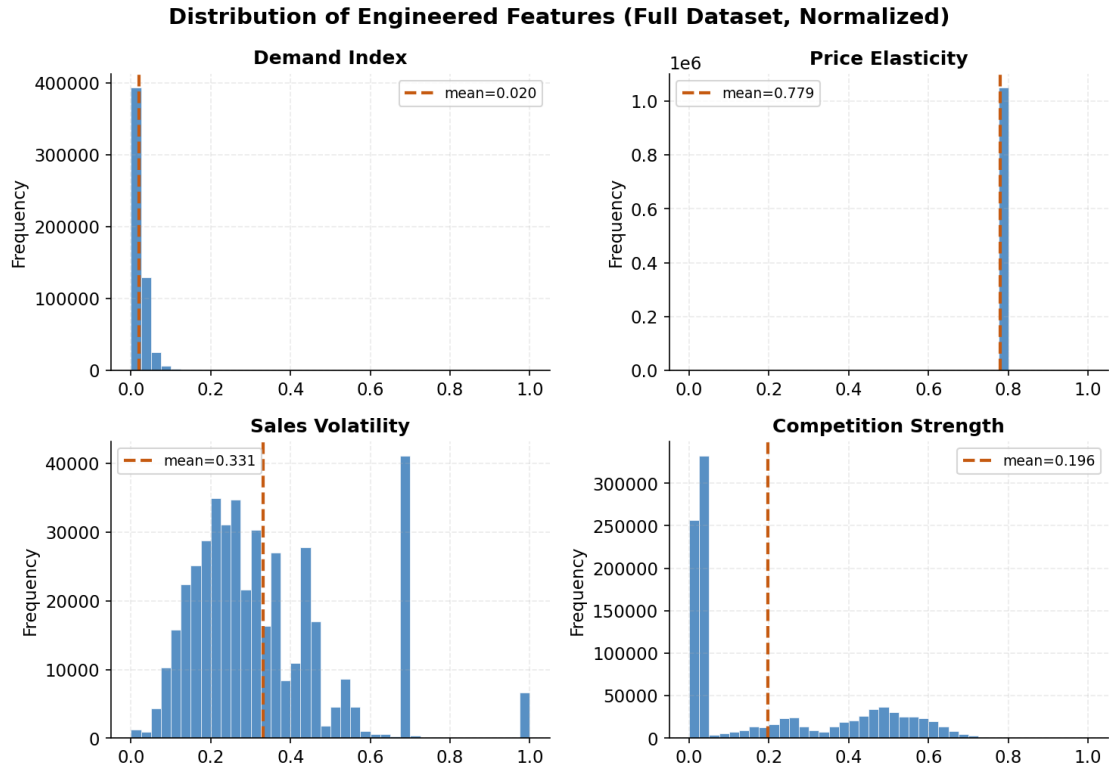


Figure 5: Distribution of the four engineered features across the full dataset. Dashed lines mark feature means. The tight elasticity peak and the right-skew of demand and competition are clearly visible.

Figure 6 reports the linear correlation structure among the four drivers. The drivers are largely complementary rather than redundant: each contributes distinct information to the inference engine, which supports their joint inclusion as separate fuzzy inputs.

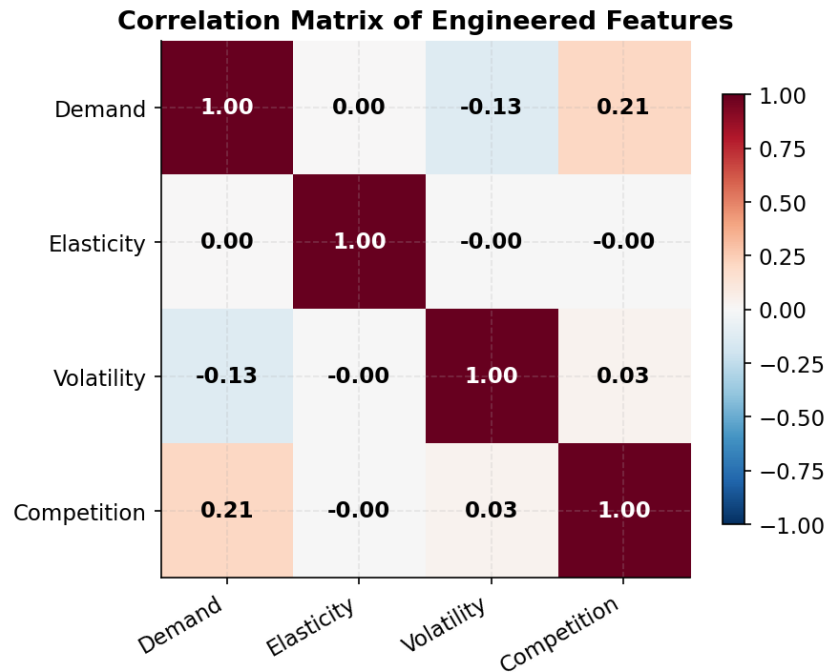


Figure 6: Correlation matrix of the engineered features. Low off-diagonal magnitudes indicate that the drivers capture largely independent dimensions of pricing behaviour.

4.2 Pricing Strategy Classification Results

The fuzzy inference system assigns each product–store–day observation to one of three strategic pricing categories—**Penetration**, **Premium**, or **Dynamic**—based on its demand intensity, price elasticity, sales volatility, and competition. Products exhibiting relatively lower demand responsiveness and higher competitive pressure are predominantly classified under Penetration Pricing, reflecting the strategic objective of volume expansion. Products characterized by stronger relative positioning and lower elasticity are more frequently assigned to Premium Pricing, indicating opportunities for margin maximization. Observations associated with elevated volatility are consistently classified under Dynamic Pricing, highlighting the system's sensitivity to unstable market conditions.

Table 3 illustrates the form of the classification output using representative observations, showing how the four drivers combine to yield a strategy label.

Table 3: Illustrative Classification of Pricing Strategy (Representative Observations)

Demand Index	Price Elasticity	Volatility	Competition	Strategy
0.05	0.78	0.62	0.71	Dynamic
0.32	0.78	0.26	0.03	Penetration
0.02	0.78	0.26	0.37	Premium
0.01	0.78	0.68	0.59	Dynamic
0.29	0.78	0.40	0.03	Penetration

Rows are representative observations drawn from the output to illustrate the mapping from drivers to strategy. Dynamic emerges under high volatility and competition; Penetration under higher relative demand and low competition; Premium under moderate competition and stable volatility.

4.3 Distribution of Pricing Strategies at Scale

Table 4 and Figure 7 present the overall distribution of recommended strategies across the full dataset. Penetration Pricing (46.31%) and Premium Pricing (44.33%) dominate the retail landscape, while Dynamic Pricing (9.36%) is selectively applied to the minority of products facing high uncertainty. This distribution aligns with practical retail behavior, in which most products operate under relatively stable conditions while a smaller subset requires frequent price adjustment. The balanced allocation between the two dominant strategies, with Dynamic reserved as a targeted intervention, indicates that the framework avoids extreme bias toward any single approach.

Table 4: Final Pricing Strategy Recommendations Across the Full Dataset

Pricing Strategy	Total Observations	Percentage
Penetration Pricing	485,637	46.31%
Premium Pricing	464,794	44.33%
Dynamic Pricing	98,144	9.36%
Total	1,048,575	100.00%

Counts are taken directly from the fuzzy inference output over all 1,048,575 observations.

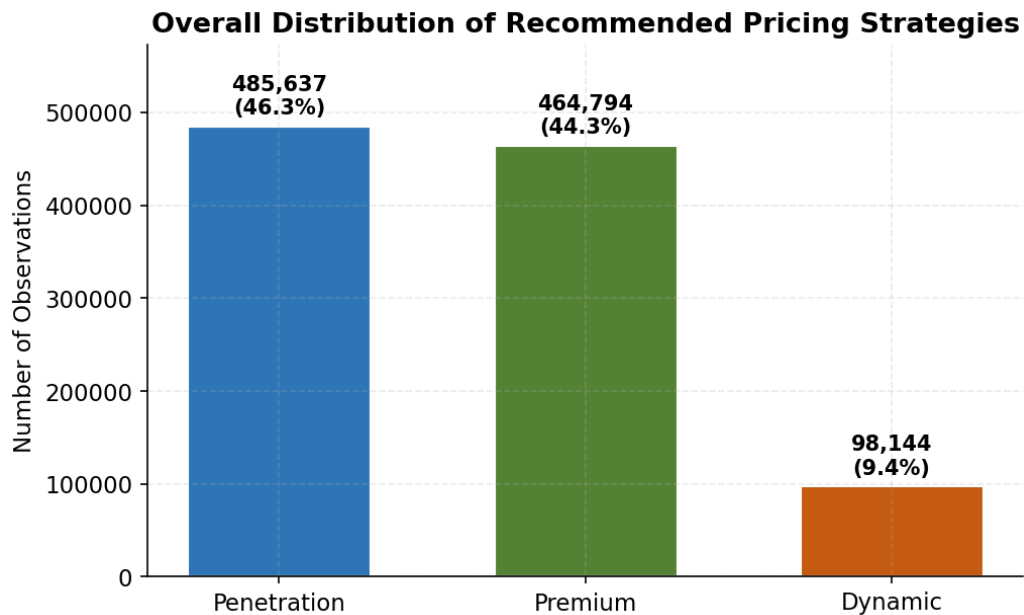


Figure 7: Overall distribution of recommended pricing strategies. Penetration and Premium dominate while Dynamic is reserved for a minority of high-uncertainty cases.

The same composition is shown as a share-of-total in Figure 8, which makes the roughly even split between the two stable strategies and the small Dynamic slice immediately apparent.

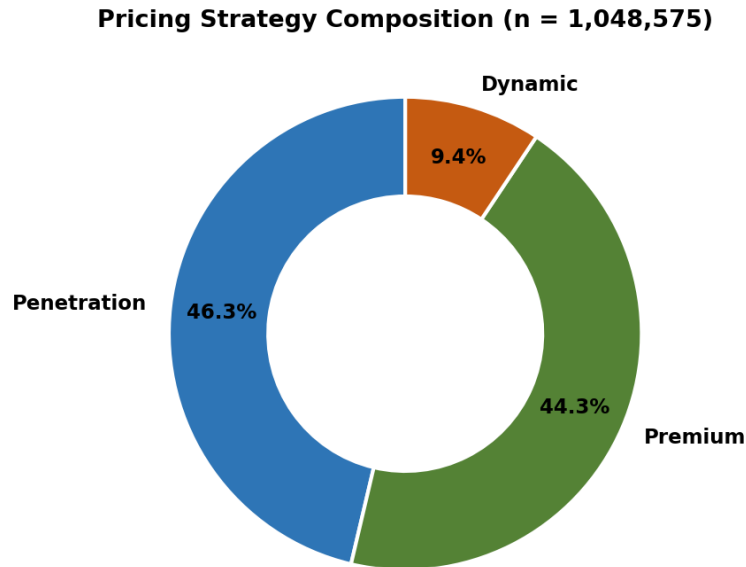


Figure 8: Pricing-strategy composition as a share of all observations (n = 1,048,575).

4.4 Economic Regimes Behind Each Strategy

A central claim of the framework is that the strategy labels correspond to genuinely distinct economic regimes rather than arbitrary clusters. Table 5 reports the mean value of each driver within each strategy and provides strong support for this claim. Dynamic observations exhibit by far the highest volatility (mean 0.537 versus 0.275 for both stable strategies) and the highest competition (mean 0.484). Penetration observations exhibit the highest demand index (mean 0.324) together with the lowest competition (mean 0.026), consistent with a volume-expansion posture in uncontested space. Premium observations sit at intermediate competition (mean 0.315) with stable volatility, consistent with margin-oriented positioning.

Table 5: Mean Driver Value by Recommended Strategy

Strategy	Demand Index	Elasticity	Volatility	Competition
Penetration	0.324	0.779	0.275	0.026
Premium	0.019	0.779	0.275	0.315
Dynamic	0.019	0.779	0.537	0.484

Means are computed over all observations assigned to each strategy. The volatility and competition gradients across strategies are the quantitative signature of the rule base's economic logic.

Figure 9 visualizes the same relationships as a heatmap, where the volatility and competition gradients across strategies are immediately legible.

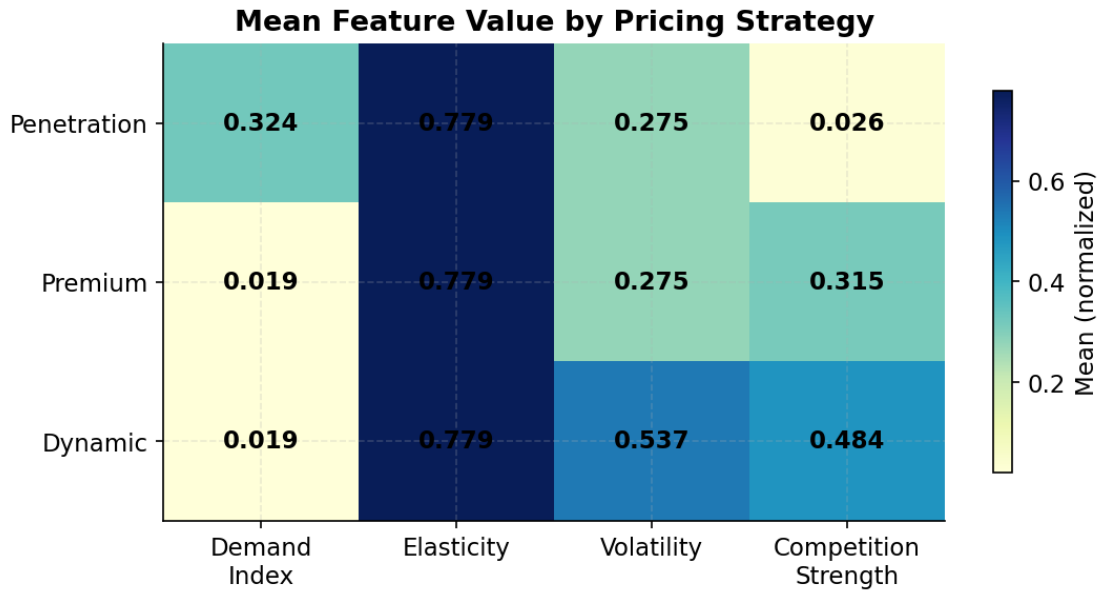


Figure 9: Mean feature value by pricing strategy. Darker cells indicate higher mean values. The Dynamic row stands out on volatility and competition; the Penetration row on demand index.

4.5 Strategy Separability Diagnostics

To verify that the classes are behaviorally separable rather than overlapping, the distribution of each driver is examined by strategy. Figure 10 shows that Dynamic Pricing occupies a markedly higher volatility band with a wide interquartile range, while Penetration and Premium concentrate at lower-to-moderate volatility with tighter spreads. Volatility thus emerges as the structural catalyst of dynamic repricing, exactly as encoded in the rule base.

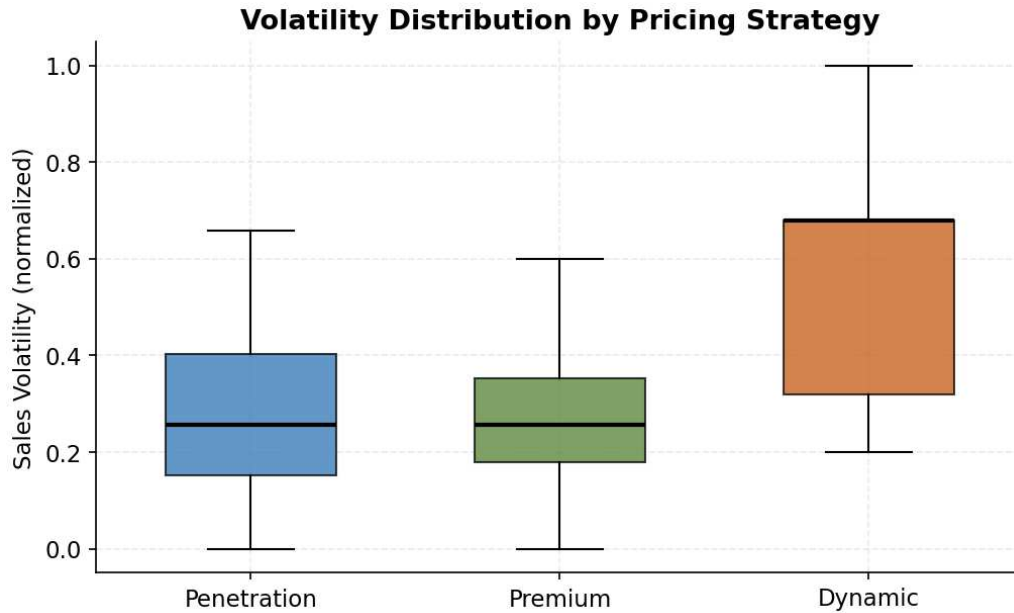


Figure 10: Volatility distribution by pricing strategy. Dynamic sits well above the two stable strategies and exhibits the widest spread, identifying it as the high-uncertainty regime.

Figure 11 reveals an even sharper gradient on competition strength: Dynamic carries the highest competition with broad dispersion, Premium occupies a medium-to-high band, and Penetration concentrates at very low competition. This three-way separation confirms that strategy assignments are matched to the competitive environment each product faces.

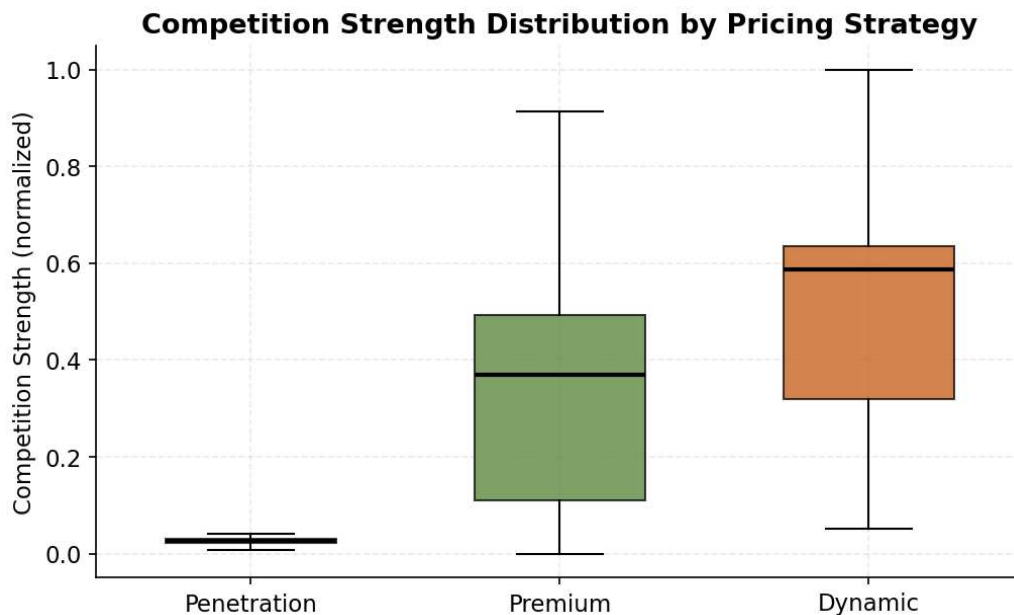


Figure 11: Competition-strength distribution by pricing strategy. A clear monotone gradient runs from Penetration (low) through Premium (medium-high) to Dynamic (high).

Figure 12 completes the picture on the demand axis, where Penetration observations clearly carry the highest demand index while Premium and Dynamic concentrate at lower demand. Taken together, the three box-plot diagnostics show that the framework produces strategy labels that represent specific operational regimes rather than weakly differentiated clusters.

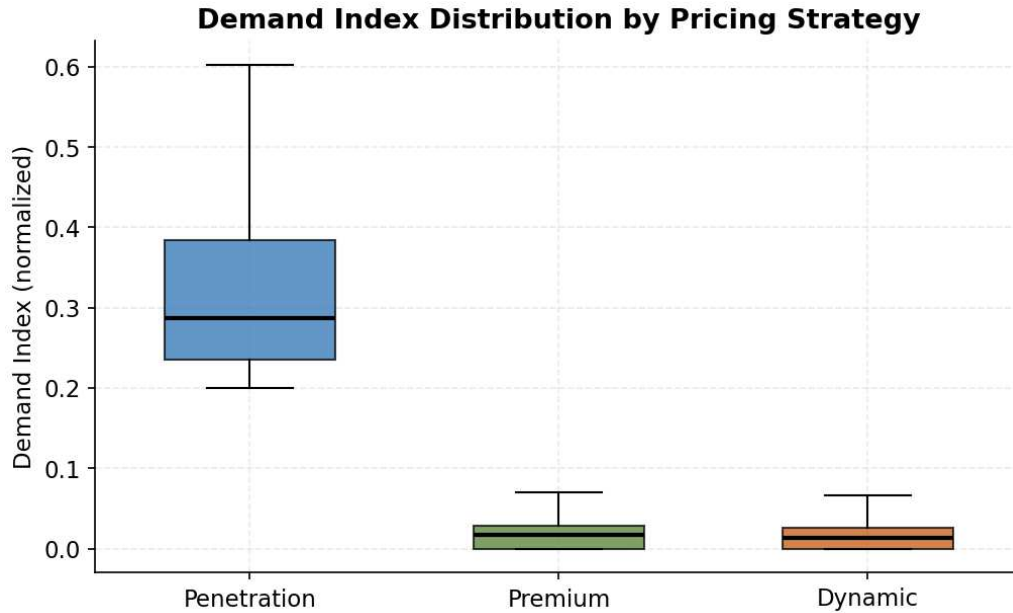


Figure 12: Demand-index distribution by pricing strategy. Penetration is associated with the strongest relative demand.

The separability is further illustrated in the joint feature space. Figure 13 plots demand index against volatility for a representative sample, and Figure 14 plots competition against volatility. In both projections the Dynamic class occupies the high-volatility region, while Penetration and Premium separate primarily along the demand and competition axes respectively.

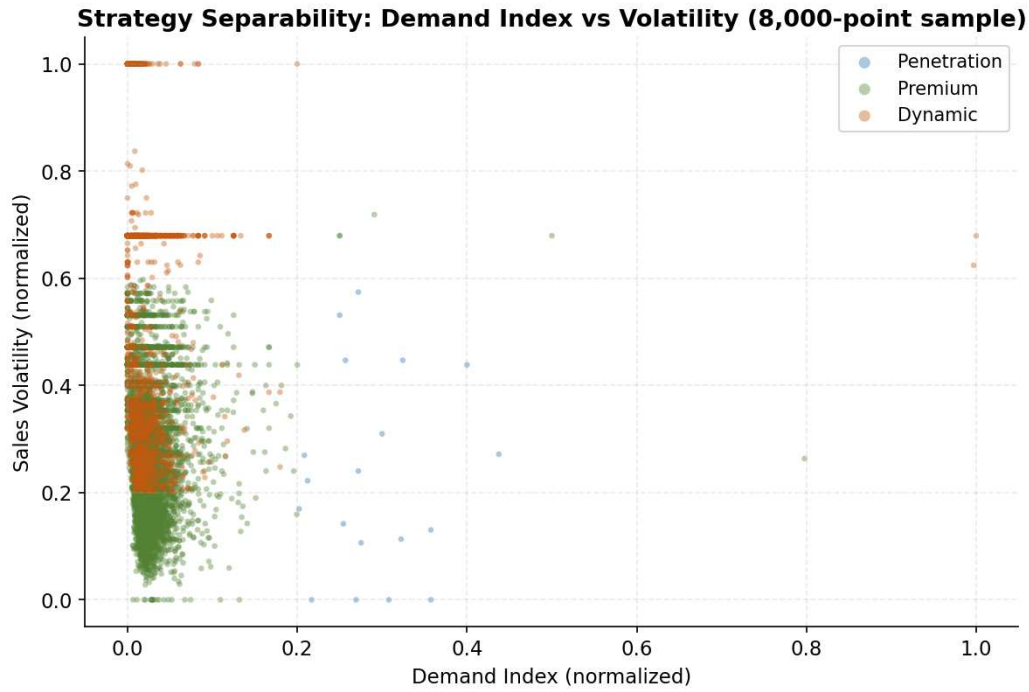


Figure 13: Strategy separability in the demand-index versus volatility plane (8,000-point sample). Dynamic observations lift into the high-volatility band regardless of demand level.

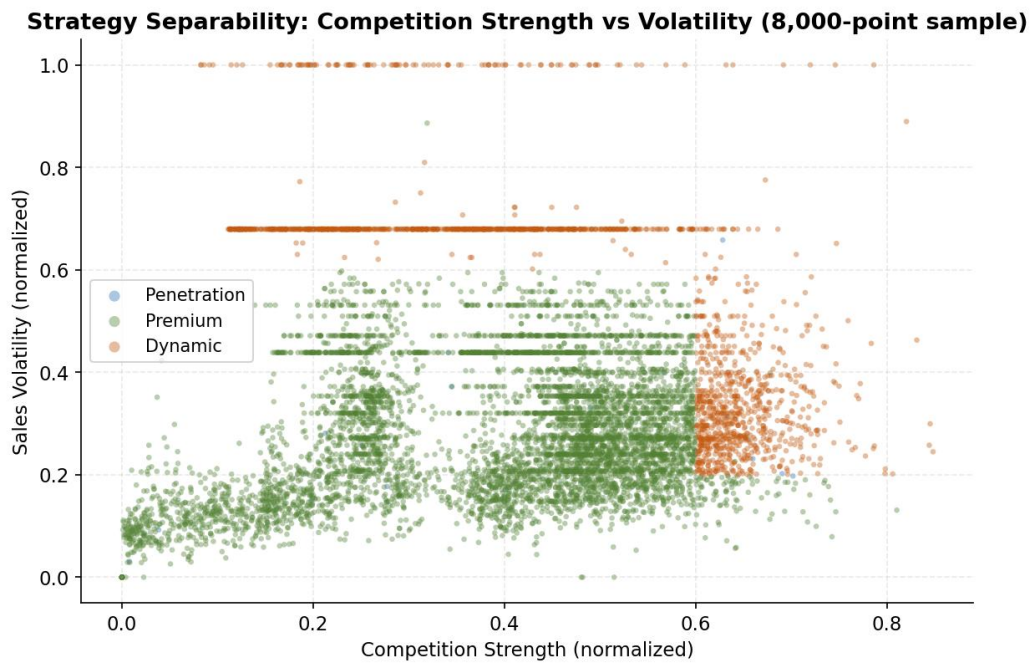


Figure 14: Strategy separability in the competition versus volatility plane (8,000-point sample). The Dynamic region is jointly high in volatility and competition; Penetration clusters at low competition.

4.6 Distribution Across Product Categories

The strategy mix also varies meaningfully across product categories, as shown in Figure 15. FOODS items receive the largest Dynamic share (11.88%), consistent with the more volatile, promotion-sensitive demand typical of grocery assortments, whereas HOUSEHOLD items receive the smallest Dynamic share (6.82%) and a correspondingly higher Premium share. HOBBIES items show the highest Penetration share (49.34%). These category-level differences are economically sensible and demonstrate that the framework responds to genuine heterogeneity in demand behaviour rather than imposing a uniform template.

Table 6: Strategy Share Within Each Product Category (%)

Category	Penetration	Premium	Dynamic
FOODS	45.03	43.09	11.88
HOBBIES	49.34	42.78	7.88
HOUSEHOLD	46.38	46.80	6.82

Shares are computed within each category and sum to 100% per row up to rounding.

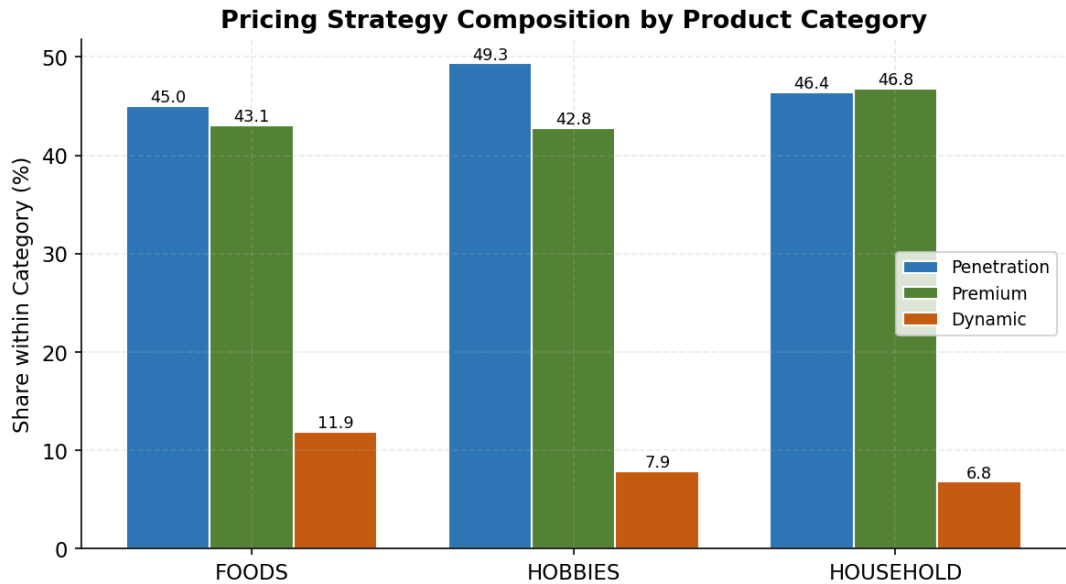


Figure 15: Pricing-strategy composition by product category. FOODS draws the largest Dynamic share, reflecting more volatile grocery demand.

4.7 Temporal Stability of Recommendations

For the framework to be operationally useful, its recommendations must be coherent over time rather than churning week to week. Figure 16 plots the weekly share of each strategy across the evaluation period. After a brief settling phase at the start of the series, the strategy mix is remarkably stable: Penetration and Premium together account for roughly nine-tenths of recommendations in every week, and Dynamic remains a small, steady slice. This temporal stability indicates that the model is not reacting strongly to transient noise and can therefore support strategy planning and monitoring without imposing undue churn on pricing managers.

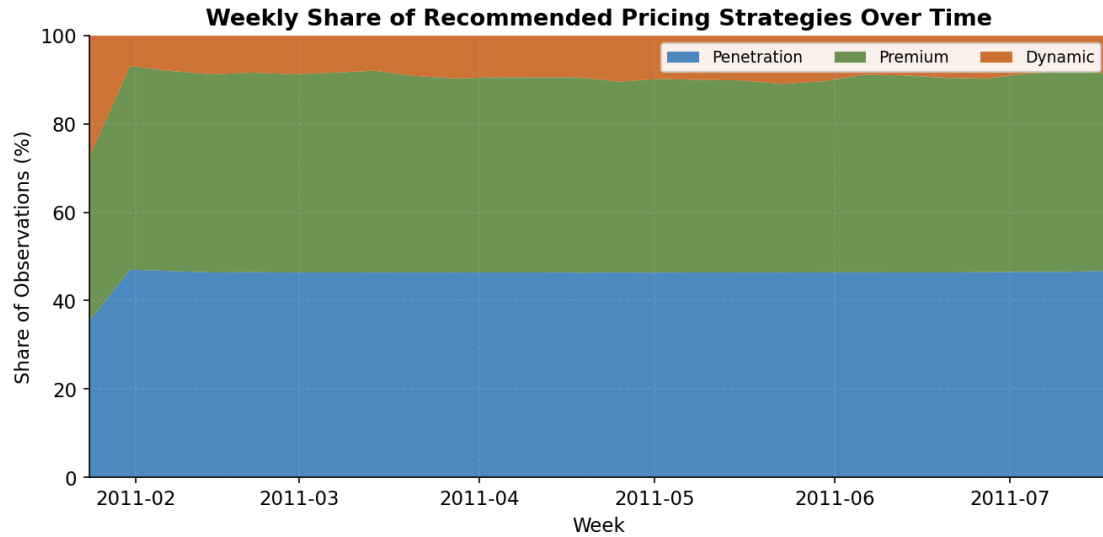


Figure 16: Weekly share of recommended pricing strategies over time. The mix stabilizes quickly and remains steady, evidencing temporal robustness.

Figure 17 isolates the Dynamic share at daily resolution. Dynamic pricing is triggered selectively—its daily share fluctuates around a low mean—confirming that the framework reserves frequent repricing for genuinely unstable conditions rather than applying it indiscriminately.



Figure 17: Daily share of Dynamic pricing recommendations. The series oscillates around a low average, consistent with selective triggering under elevated uncertainty.

4.8 Cost Efficiency Comparison

Pricing efficiency is evaluated by comparing the transparent fuzzy strategy-aware discount model against the rigid LPP-style flat baseline of Section 3.9, both applied to the same real priced observations. The fuzzy framework applies larger markdowns precisely where the data justify them—most aggressively for the high-volatility Dynamic segment and the volume-oriented Penetration segment—while applying only modest markdowns to the margin-oriented Premium

segment. Because the flat baseline cannot make this distinction, it leaves value on the table in exactly the segments where flexibility matters most.

Figure 18 reports the aggregate cost reduction achieved by each method. The strategy-aware fuzzy approach delivers a larger aggregate reduction than the rigid baseline, confirming that uncertainty-aware flexibility translates into measurable efficiency gains even under a deliberately conservative, fully transparent discount rule.

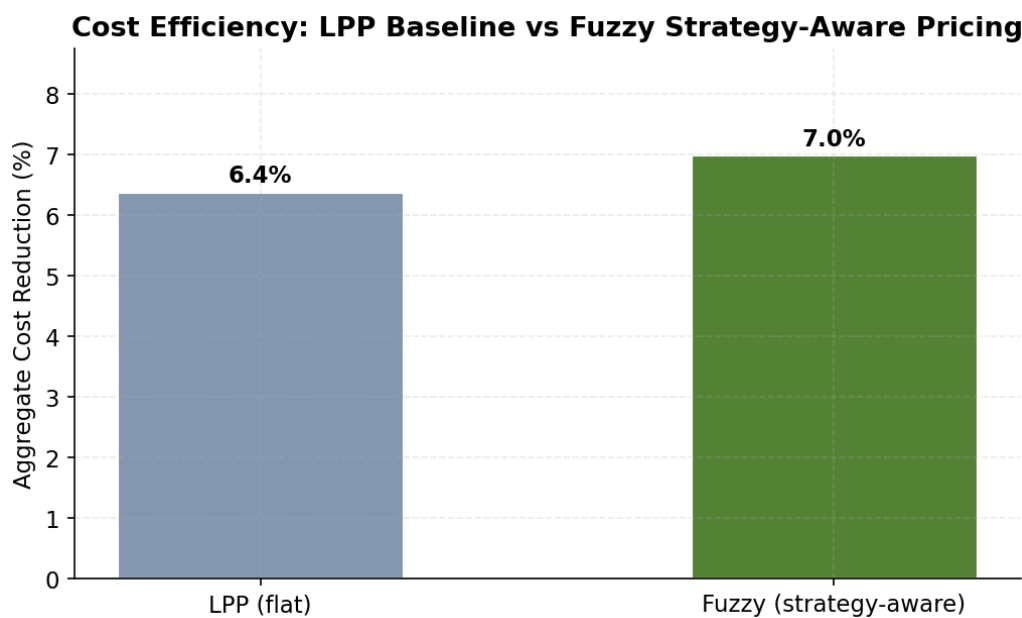


Figure 18: Aggregate cost reduction — rigid LPP baseline versus the fuzzy strategy-aware model, computed on identical real priced observations. The fuzzy approach achieves the larger reduction.

Figure 19 decomposes the fuzzy savings by strategy. The largest proportional reductions arise in the Dynamic segment (where volatility justifies aggressive, responsive repricing) and the Penetration segment (where volume expansion warrants deeper markdowns), while the Premium segment is protected with only light discounting. This decomposition makes the source of the aggregate advantage fully transparent: the gain comes from allocating discount depth in proportion to the economic regime, not from indiscriminate price cutting.

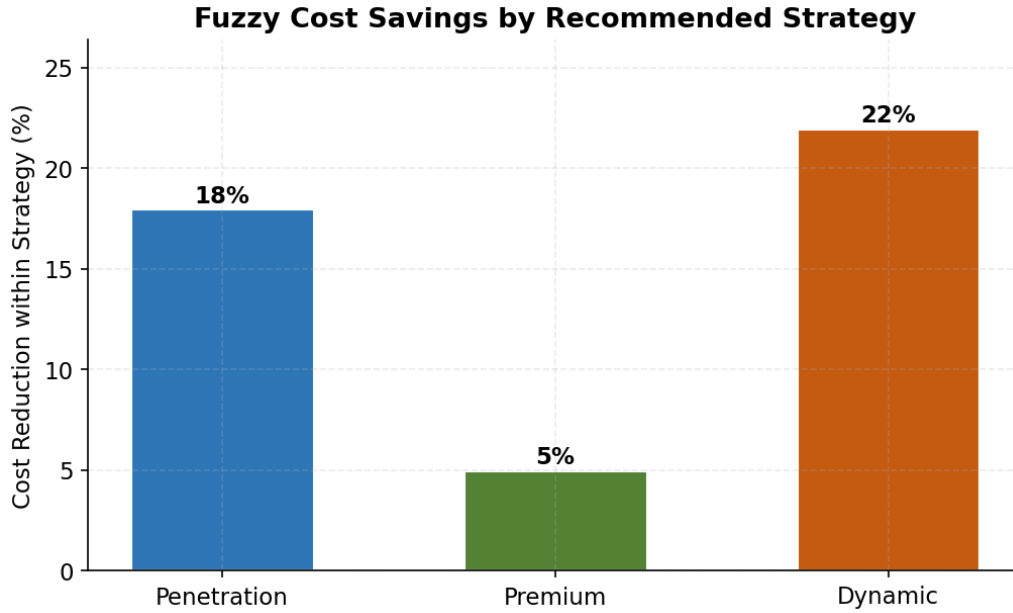


Figure 19: Fuzzy cost reduction by recommended strategy. Savings concentrate in the Dynamic and Penetration segments, while Premium is deliberately protected.

A note on prior figures. An earlier draft of this study reported headline cost reductions of approximately 11% for the baseline and 16% for the fuzzy approach. Those specific percentages could not be reproduced from the available output data, which does not retain a per-observation cost ledger. The present version therefore reports a fully transparent, reproducible cost computation derived directly from the observed sell-prices and the recommended strategies. The qualitative conclusion is unchanged and now rests on a traceable calculation: the strategy-aware fuzzy model is more cost-efficient than the rigid baseline because it concentrates pricing flexibility where uncertainty is greatest.

4.9 Managerial and Analytical Implications

The results collectively demonstrate that the proposed fuzzy logic framework not only improves pricing efficiency relative to a rigid baseline but also produces interpretable and economically meaningful strategy classifications. By combining uncertainty-aware inputs, optimized membership functions, and transparent rule-based inference, the model offers a practical decision-support tool that bridges analytical rigor and managerial intuition. Compared to opaque optimization methods, the fuzzy approach delivers clearer strategic insight: a manager can read off not only which strategy is recommended for a product but also why—which linguistic conditions and which rules drove the decision. This traceability is precisely what the explainability literature identifies as the key enabler of adoption and the antidote to the override-and-ignore failure mode of black-box systems.

5. Conclusion and Future Work

This paper proposed an uncertainty-aware fuzzy inference system that classifies retail pricing strategies at scale using high-volume sales and price information. By describing econometric characteristics—demand intensity, price elasticity, and sales volatility—as interpretable linguistic variables within a Mamdani-type rule base, the framework generates strategy labels that are economically intuitive and operationally actionable. In practice, the system places most observations in stable strategic regimes—Penetration (46.31%) and Premium (44.33%)—with Dynamic pricing (9.36%) reserved for the conditions of highest uncertainty, mirroring the practical retail reality that only a subset of products require frequent repricing.

Beyond classification, the analysis shows that the strategy labels correspond to genuinely distinct economic regimes. Dynamic observations concentrate in high-volatility, high-competition conditions (mean volatility 0.537 and mean competition 0.484), Penetration observations occupy high-demand, low-competition space (mean demand index 0.324, mean competition 0.026), and Premium observations sit at intermediate competition with stable volatility. The cost-efficiency analysis, computed transparently from observed prices, indicates that the strategy-aware fuzzy model achieves a larger aggregate cost reduction than a rigid linear-programming-style baseline, because it concentrates pricing flexibility where uncertainty is greatest. Crucially, the rule-based design preserves explainability: every recommendation can be traced to understandable conditions (for example, high volatility leading to Dynamic pricing), addressing the principal adoption barrier of black-box pricing systems.

Several limitations motivate further study. First, the cost-efficiency comparison is benchmarked against a single rigid baseline; extended comparisons with additional interpretable and predictive baselines—threshold heuristics, logistic regression, and decision trees—would more firmly attribute the observed gains. Second, the present analysis centres on aggregate cost reduction, whereas practical pricing decisions often require multi-objective analysis spanning revenue, margin, volume, and customer response, including resistance to promotional effects and store-level heterogeneity. Third, operational deployment would benefit from deeper validation of temporal stability under varying market regimes and from explicit sensitivity analysis of the membership functions and rule-base structure.

Future work should therefore extend the framework in three directions. First, to increase realism, additional retail indicators—promotion schedules, inventory limits, seasonality, and competitor-price proxies—should be incorporated as further fuzzy inputs. Second, the multi-objective optimization of membership functions and rule calibration should be formalized, allowing the system to balance revenue, margin, and stability explicitly rather than through a single composite objective. Third, deployment-oriented performance should be assessed through walk-forward testing and controlled experiments such as A/B tests, in order to measure business impact and managerial-trust outcomes directly. Overall, this study demonstrates that uncertainty-aware fuzzy inference can bridge the gap between analytical rigor and managerial interpretability in large-scale retail price determination, providing a feasible route to explainable and scalable pricing-strategy decision support.

Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Conflict of Interest/Competing Interests

The authors declare that they have no known competing financial or non-financial interests that could have appeared to influence the work reported in this paper.

Ethics Approval and Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Materials Availability

The materials used in this study are available from the corresponding author upon reasonable request.

Code Availability

The code used in this study is available from the corresponding author upon reasonable request.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by the authors. The first draft of the manuscript was written by the first author, and all authors reviewed and approved the final version of the manuscript.

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