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EROSKI: Artificial intelligence for pricing and electronic shelf labels

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What began in 1969 as a coalition of 10 small Basque cooperatives became one of Spain's most distinctive grocery retailers. Founded in Elorrio, Biscay, and named from the Basque words *erosi* ("to buy") and *toki* ("place"), Eroski grew with a clear identity: regional roots, cooperative ownership, and a belief that retail could serve both customers and communities.

More than 50 years later, that model was tested. Spain's grocery market had become fiercely price sensitive, competitors were becoming more data-driven, and consumers expected low prices. Eroski needed to protect margins and modernize its pricing capabilities without weakening the cooperative values that had long set it apart.

For CEO Rosa Carabel, the tension was clear: "Social responsibility without economic profitability is very difficult."[1] As Eroski began to embrace advanced analytics, algorithms, and automation, the central question was not simply whether AI could improve prices; it was whether digital transformation could strengthen the cooperative's human and social mission rather than dilute it.

Eroski's background

Eroski operates as a consumer–worker cooperative, jointly owned and governed by employees and customers. By 2023, 8,989 of its 27,426 employees were cooperative members holding voting rights and sharing the company's profits. For Eroski, this model reflected a broader philosophy: Value is created collectively and should benefit people, communities, and society. As CEO Rosa Carabel emphasized, "If we weren't a cooperative, if we didn't have the commitment and involvement of all those people, we wouldn't be here."[2]

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Eroski manages 1,524 locations, including 1,406 food retail outlets—1,353 supermarkets and 36 hypermarkets—along with 118 nonfood businesses, such as travel agencies, opticians, and sporting goods stores. The company also operates an online platform, maintaining its strongest foothold in the Basque Country, Navarre, the Balearic Islands, and Catalonia (see Exhibit 1). Despite economic headwinds, Eroski achieved strong financial results, reporting €5.19 billion in revenue, €108.6 million in net profit, and €259 million in operating income in 2023 (see Exhibit 2).

The problem: The opportunity

Until recently, Eroski had relied on a fully manual process to set prices for nearly 29,000 products, ranging from fresh goods to packaged items. Each category manager oversaw two to three product groups using intuition, spreadsheets, and simple heuristics to make pricing decisions. Without access to real-time demand data, financial models, or elasticity insights, decisions were guided largely by habits and assumptions about customer behavior.

"We used to calculate prices in Excel using fixed multipliers. It worked for a time, but it wasn't scalable anymore", Mónica Hermosilla, digital transformation manager, recalled. These limitations became increasingly evident as product assortments expanded and market competition intensified.

Recognizing the need for change, Eroski partnered with Deloitte in 2019 to introduce AI into its pricing strategy. AI in this context enables systems to learn from data and make decisions autonomously. With thousands of stock keeping units (SKUs) subject to shifting costs, competitor moves, and demand volatility, AI allowed companies to make pricing decisions that are faster, smarter, and more consistent.

The collaboration was structured as a revenue-sharing model, linking Deloitte's compensation to the performance of the pricing tool and ensuring shared accountability for outcomes. Together, they developed a minimum viable product (MVP), an early version of an AI-driven pricing model to test in selected stores and categories. However, the first iteration never reached implementation. "We didn't even bring it into stores," Mónica said. "We had too many doubts and didn't feel comfortable with it."

Rather than abandoning the project, Deloitte restructured its team and the revised model was piloted in October 2020. The results were clear: Stores using the AI-based system saw improvements in both sales and profit margins compared to those without. What had started as a cautious experiment evolved into one of Eroski's most compelling transformations, ultimately leading to the rollout of AI-based pricing across its entire retail network.

Optimal price

This algorithmic pricing model uses machine learning methods to estimate price elasticity—how demand for each product responds to price changes—and predict sales. The model's core logic can be summarized as follows:

$$\log(1 + Q_{\text{ist}}) = \alpha + \beta \log(1 + p_{\text{ist}}) + \gamma_{\text{s}} + \gamma_{\text{t}} + +X_{\text{ist}} + \varepsilon_{ist}$$

where Q_{ist} denotes units sold for SKU i in store s during week t, p_{ist} is price, β captures price sensitivity, and $\gamma_s$and γ_t absorb store- and week-level effects. These dummies controlled for systematic differences across locations (e.g., store size, neighborhood characteristics) and time patterns (e.g., promotions, seasonality, holidays), helping isolate the impact of price changes on demand. To further improve accuracy, the system also incorporated more than 15 additional

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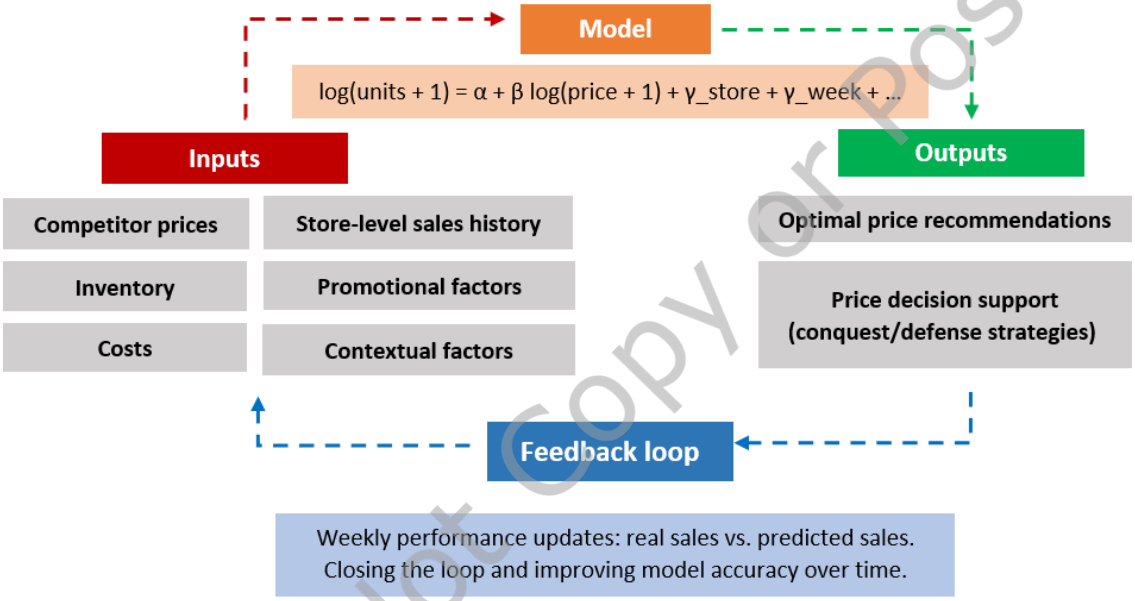
explanatory variables (captured by X_{ist}) from both internal and external sources, including two and a half years of historical sales data, promotional intensity, assortment structure, competitor prices, VAT changes, and margin information from the previous six months.

Elasticity values were recalculated weekly, ensuring that price recommendations remained aligned with market conditions. Accuracy was then validated by comparing predicted sales against realized sales, creating a feedback loop that continuously improved performance (see Figure 1). Internal benchmarks showed that the model achieved over 95% accuracy across more than 15,000 SKU-level models.

Figure 1
Schematic of the pricing model



Source: Prepared by the author.

Using these inputs, the system translated the statistical model into actionable commercial insights by constructing demand, revenue, and profit curves for each product. For a candidate price p, predicted demand is denoted by $\mathrm{Q(p)}$. Revenue is computed mechanically in the following manner:

$$\mathrm{Revenue(p)} = \mathrm{p} \times \mathrm{Q(p)}$$

where p is price and $Q(p)$ is predicted demand. Profit is defined as follows:

$$\mathrm{Profit(p)} = (\mathrm{p} - \mathrm{c}) \times \mathrm{Q(p)}$$

where c denotes unit cost.

Figure 2 illustrates these relationships for one example product. The horizontal axis shows the price Eroski could charge, while the vertical axis measures monetary outcomes in euros. The blue curve represents revenue, while the orange curve shows profit. As price increases, revenue initially rises because each unit generates higher income, but eventually declines as demand drops sharply. This creates the inverted U-shape observed in the revenue curve.

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