Digital Transformation for Nostalgic Product Substitution Decisions: Monte Carlo Simulation and Machine-Learning Metamodels

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Abstract*– When an exporting firm depends on a high-turnover nostalgic product that functions as a traffic generator, uncertainty in its supply becomes a strategic risk. This paper proposes a decision-support model, framed within the firm's digital transformation, to assess whether the product should be replaced by a locally contract-manufactured alternative with equivalent brand positioning and flavor. Monte Carlo simulation generates 10,000 synthetic scenarios over a five-year horizon using thirteen triangularly distributed variables. These variables are calibrated with open macroeconomic data retrieved automatically from World Bank application programming interfaces (APIs). Random Forest and Gradient Boosting serve as machine-learning metamodels of the simulator to identify nonlinear interactions and critical variables within the sampled domain. Results yield a 69.77 % probability of success, an average net present value of L 295,052, a mean internal rate of return of 62.66 %, and an average payback period of 2.07 years. Package price, initial demand, and variable cost dominate project performance. However, the downside is material: the fifth percentile of the distribution reaches L −497,870, and roughly three of every ten scenarios destroy value. The framework converts supply uncertainty into transparent, reproducible, and actionable managerial criteria.

Keywords-- metamodeling; supply chain resilience; investment appraisal under uncertainty; financial risk; remittances and diaspora demand.

I. Introduction

This article addresses the management of nostalgic products from a systemic approach to marketing and internationalization [1], [2]. Such an approach is relevant because decisions to replace a product of high commercial value are not isolated; they also impact the product portfolio, the relationship with the consumer, the supply chain, and cash flow. Under this framework, therefore, financial risk assessment is not an end in itself, but rather a strategic decision-making criterion [3] that allows the evaluation of commercial resilience and the continuity of the portfolio as decisive factors for international competitiveness [4]–[6]. Consequently, Monte Carlo simulation and machine learning are used as decision-support tools rather than as a financial analysis detached from the company's strategy [7].

Small and medium-sized exporting companies in Central America operate with narrow margins, numerous financial constraints, and marked vulnerability to certain changes in the business environment [8], [9]. This vulnerability is exacerbated by dependence on concentrated suppliers, multiple exposures to shocks or foreign exchange rate fluctuations, inflation, and macroeconomic factors [10]. Maintaining sales of certain products is a condition for commercial survival [3], [4], [11]. The company under analysis faces a dilemma regarding its product portfolio: a nostalgic soft drink with high turnover that is difficult to find and heavily dependent on a third party. Consequently, there is a significant risk of supply disruptions and revenue loss, which is why the proposal is to develop a new product based on authenticity that can meet this demand [12], [13].

In these nostalgic markets, the value of the product lies not only in the attribute itself but also in its cultural roots and symbolic continuity, which originate both among local consumers and within certain segments of migrant communities [14], [15]. This consumption also circulates extensively in migrant economies through remittances, as well as within the diaspora, which constitutes a significant transnational segment with consumption habits linked to their country of origin [16], [17]. In Honduras, remittances exceed USD 9 billion, representing nearly 25 % of GDP [18]. This represents sustained demand for goods associated with national identity.

Retail literature describes a high-turnover product whose value is based not only on the unit margin but also on its ability to attract customers and generate cross-sales; such products are referred to as "traffic generators." [19], [20]. Using an ABC classification, the product offering can be structured, distinguishing certain products as Category A—which drives sales activity—and others, such as functional items or substitutes, that generate traffic [21]. The strategic value of a traffic generator becomes critical when its supply fails, leading to stockouts that not only cause inventory shortages but also prompt brand switching, erode loyalty [22], and, according to some evidence, affect the firm's value [11].

This article conducts a portfolio analysis, proposes investment criteria, and evaluates the strategic substitution of a high-value nostalgic product [15] with a locally contract-manufactured beverage under equivalent brand positioning and a comparable flavor profile. The objective is to reduce shortage risk and establish a new business unit, while providing a replicable procedure for other investment decisions [10]. The proposed fruit-flavored carbonated beverage has strong cultural roots and is packaged in 12 units of 600 mL at a contract manufacturing cost of L 120 per package. The decision is far

from trivial: the substitute must be both financially viable and culturally legitimate.

To what extent does this integrated model—combining Monte Carlo simulation and a machine learning metamodel, along with open macroeconomic data—support a decision to strategically replace a nostalgic product that generates high traffic, thereby reducing the risk of shortages and potentially enabling a new business unit in an emerging Central American economy?

Accordingly, the study aims to design a probabilistic model for financial and strategic evaluation that incorporates shortage risk, nostalgic acceptance, diaspora demand, logistics costs, taxation, and macroeconomic uncertainty.

II. Theoretical Framework

A. High-traffic products and strategic changes to replace them

Product substitution is always a strategic decision—unlike a simple purchase order—that reconfigures the company's resources and portfolio composition [5] and affects the customer experience and brand positioning [23]. With nostalgic products, we are not only dealing with the product's value; rather, this value goes beyond the functional by incorporating authenticity and cultural recognition, in addition to generating emotional loyalty. They function as an intangible asset capable of sustaining a competitive advantage that is difficult to imitate [13]. This explains why a company cannot treat the discontinuation of an iconic product as a routine logistical problem.

Retail economics provides this specific concept for certain types of goods. A high-traffic-generating product is characterized by its ability to attract many customers and trigger the purchase of other complementary products. Thus, the business's contribution stems more from the sales it drives than from its own margin [19]. This effect is particularly pronounced when the retailer has a broad product portfolio that allows for cross-selling, as the product considered the "anchor" increases the average transaction value and the frequency of visits [20]. Consequently, removing or failing to restock a traffic driver will not only reduce direct sales. In practice, weakening the sustained cross-selling effect will reduce purchase frequency and sales across the entire product portfolio [24], an effect that will be further jeopardized if a stockout leads customers to switch stores or brands [22].

In supply chain management, it is noted that concentrating sales on a few products or suppliers can also increase exposure to disruptions [10]. In ABC classification analysis, which helps visualize this risk, it is observed that Category A products account for the majority of commercial activity, while Category B and C products serve as substitutes or traffic drivers [21]. Interpreted in this way, the classification sometimes goes beyond being merely an inventory control tool and becomes a strategic decision-making tool capable of identifying which products safeguard business continuity in the event of supply failures—the cost of which at the firm level is measurable [11].

B. Cultural Roots and Nostalgic Product

Nostalgic products combine functionality with symbolic value. This nostalgia influences purchase intent, brand loyalty, and the persistence of consumption habits associated with cultural roots [15]. In migrant communities, the product fulfills various additional functions. It acts as an emotional bridge to the country of origin [14]. This symbolic significance is both the source of the product's value and the category's point of vulnerability, because any change perceived as a loss of authenticity can erode the emotional bond that sustains demand [25].

Therefore, the substitution decision must be evaluated using criteria that extend beyond financial performance, particularly the substitute's authenticity and emotional connection. It is not enough for the new brand to be profitable; consumers must also perceive it as authentic and culturally consistent with what the original product represented. Research on brand authenticity supports this logic by showing that authenticity is a relational asset that firms deliberately build and manage and that it influences willingness to pay in meaning-rich markets [12], [13]. In this study, this dimension is incorporated through the nostalgic acceptance factor: a substitute that is profitable on paper may still fail if the market perceives it as an imitation lacking legitimacy.

C. Monte Carlo simulation and uncertainty

In deterministic methods, investment evaluation yields a single value, such as NPV or IRR, and therefore obscures part of the variability inherent in new projects. Monte Carlo simulation overcomes this limitation by propagating uncertainty in the input variables through the model and generating a distribution of possible outcomes, including the probabilities of success and loss and the sensitivity of each variable [26]. It is widely used to evaluate investment projects in sectors such as energy, mining, and agribusiness [27]–[30]. In this study, Monte Carlo simulation operates as a scenario generator: it produces a synthetic dataset representing possible project behavior under the stated assumptions. These scenarios are not empirical observations but realizations of the financial model.

A key methodological consideration is the selection of probability distributions for uncertain variables when extensive historical series are unavailable. The triangular distribution provides a transparent representation through three expert-judgment parameters: minimum, most likely value, and maximum, making it suitable for new-product decisions [31]. The study uses 10,000 iterations and a fixed seed so that the metrics converge to stable estimators and the results remain reproducible—an essential requirement when simulation is used as a decision-support instrument rather than as an opaque numerical exercise.

D. The Metamodel: Machine Learning as a Surrogate for the Simulator

Machine learning complements the simulation by approximating the response surface that the simulator itself defines. The relationships are established by the financial model; the metamodel learns them in a form that supports variable-importance ranking and the detection of interactions, which the raw simulation output does not expose directly. Among tree-based models, Random Forest and gradient

boosting machines are well-suited for tabular financial risk problems because they model interactions and nonlinear effects between variables. They also estimate the relative importance of variables [32]–[34]. When applied to simulation results, this approach allows us to predict the NPV using input variables and to verify that the outcome structure is interpretable and not random [34]. In comparing Spearman's correlation coefficient with variable importance, ensemble models prove to be conceptually valuable. Spearman's correlation identifies monotonic, direct relationships between each variable and the outcome [35], whereas the tree model captures interactions that bivariate analysis fails to detect [32]. The statistical literature acknowledges that these two measures may differ and that interpreting them together is more informative than considering either one separately [36], [37]. For business management, this dual perspective will make it possible to distinguish between variables related to profitability and those related to specific successes or the failure of the project.

Once the scenarios are generated, machine learning performs a specific function by acting as a surrogate model for the simulator. In computational experiments, a surrogate function is fitted—one that is faster and more manageable—to emulate the response of a costly or opaque model [42], [43]. The metamodel will not validate the Monte Carlo simulation nor verify its accuracy: it will learn the response surface that the simulator defines between inputs and the NPV, making it interpretable in terms of the importance of interactions and variables.

The metamodel is trained on scenarios sampled within the ranges and distributions shown in Table 1; thus, its predictive validity is confined to the experimental domain. The surrogate model interpolates within the sampled domain; it does not extrapolate beyond it. A price below L 160 or a demand exceeding 21,042 packages per year falls outside the explored space, and at those points, the predictions lack support.

E. Migration, the diaspora and remittances

This link between migration, remittances, and nostalgic consumption is important for gauging demand. In macroeconomics, it is well documented that remittances affect disposable income, consumption, and household well-being in emerging economies [16]. Research on internationalization indicates that diaspora networks act as a channel for the expansion of SMEs by providing market knowledge, trust, and access to distribution in the destination country [17]. This is why the model does not treat remittances as a separate macroeconomic variable, but rather as a proxy for purchasing power and the relative size of diaspora demand, incorporated using official open data [18], [38].

F. Digital Transformation

The digital transformation of SMEs does not end with the adoption of software. It involves developing data capabilities that will support systematic decision-making [39]. In the context of digitization, this takes the form of an infrastructure or architecture that integrates advanced analytics, simulation, and machine learning with open data and APIs automatically fed by application programming interfaces. This approach is consistent with recent proposals that integrate artificial intelligence and operations research for investment decision-making in emerging contexts [40]. Interpreted as a dynamic capability, this infrastructure transforms a static model into a living, auditable, and updatable system; it is one of the article's key contributions, as it brings high-level analytics to a company with limited resources without sacrificing rigor or traceability

III. Methodology

This research employs a machine learning approach, using Monte Carlo simulation for generating the dataset. The model is constructed with a five-year horizon, 10,000 iterations, and triangular distributions for the uncertain variables based on [31]. Operational data from the case include a 600-mL bottle, 12 bottles per package, and a contract manufacturing cost of L 120 per package. A container capacity is 21 pallets with 167 package each. The imported label costs USD 0.05 per bottle, and the initial trademark registration fee is L 22,000. The minimum production batch is 12,000 liters, equivalent to 1,666.67 packages. These values constrain the decision space to physically feasible ranges and prevent the simulation from exploring impossible combinations.

A. Causal Relationships

The stochastic variables of the model are summarized according to triangular ranges (minimum, mode, and maximum), as well as the unit of measurement; see Table 1.

Table 1. Stochastic variables of the strategic substitution model

Variable	Min.	Mode	Max.	Unit
Base demand Y1	10,521	14,028	21,042	pkg./year
Selling price	160	180	210	L/package
Manufacturing cost	112	120	132	L/package
Label	0.045	0.050	0.060	USD/unit
Exchange rate	24.20	24.75	25.50	L/USD
Logistics cost	6	10	18	L/package
Fixed costs	90,000	140,000	240,000	L/year
Demand growth	0 %	5 %	10 %	annual
WACC	12 %	15 %	20 %	annual
Nostalgia acceptance factor	0.70	0.90	1.10	mult.
Migration/remittances factor	0.80	1.00	1.20	mult.
Shortage factor	0.85	1.05	1.30	mult.
Cost inflation	1.00 %	2.20 %	3.25 %	annual

The central causal relationship begins with a shortage of the original product, which creates an opportunity for substitution. Nostalgic acceptance influences expected demand, which in turn affects cash flows, NPV, IRR, payback period, and ultimately the investment decision. Nostalgic acceptance, migration/remittances, and shortage opportunity multiply baseline demand; therefore, the model does not assume that every substitution is valid. Both sufficient nostalgic acceptance and an adequate commercial margin are required to create value.

B. Model Formulation.

This model integrates the commercial, operational, tax, and financial dimensions over a five-year time horizon. It is detailed as follows:

Let i = 1 and N be the iteration index (N = 10,000) and t = 1, when T be the year in the time horizon (T = 5). For each iteration, the thirteen variables in Table 1 are drawn from their respective triangular distributions. With a, m, and b denote the minimum, mode, and maximum, sampling is performed by inverting the cumulative distribution function:

$$X = a + \sqrt{[\, u\,(b-a)\,*(m-a)\,]} \text{ if } u < (m-a)/(b-a) \quad (1)$$

$$X = b - \sqrt{[\,(1-u)\,(b-a)\,(b-m)\,]} \quad (2)$$

where U (0,1). The demand for the first year, D_1, results from scaling the baseline demand D_0 by the three strategic factors: nostalgic acceptance (φ_n), migration and remittances (φ_m), and opportunity due to stockouts (φ_s):

$$D_1 = D_0 \cdot \varphi_n \cdot \varphi_m \cdot \varphi_s \quad (3)$$

Demand in subsequent years grows at the rate g, such that $D_t = D_1\,(1+g)^{(t-1)}$. The unit variable cost per package, c_v, includes the manufacturing cost (c_m), the cost of the imported label (c_e, in dollars, converted at exchange rate e for the q = 12 units in the package), the prorated cost of the pallet (c_p divided among the k = 167 units it carries), and the logistics cost (c_l):

$$c_v = c_m + (c_e \cdot e \cdot q) + (c_p / k) + c_l \quad (4)$$

The pre-tax profit for year t, U_t, as well as variable and fixed costs, are scaled each year by cost inflation π, calibrated to observed inflation.

$$U_t = [\, p - c_v\,(1+\pi)^{(t-1)}\,] \cdot D_t - CF\,(1+\pi)^{(t-1)} \quad (5)$$

The tax burden combines an income tax (τ_1 = 25 %) on positive profit and a solidarity contribution (τ_2 = 5 %) levied only on the surplus above the threshold $\bar{U}$ = L 1,000,000:

$$T_t = \tau_1 \cdot \max(0, U_t) + \tau_2 \cdot \max(0, U_t - \bar{U}) \quad (6)$$

The net cash flow for the year is $FCN_t = U_t - T_t$. Discounting these cash flows at the cost of capital r and subtracting the initial investment I_0 yields the net present value:

$$NPV = -I_0 + \Sigma_{t=1}^{T} FCN_t / (1+r)^t \quad (7)$$

The internal rate of return is the root r* that makes expression (7) equal to zero, and the payback period corresponds to the first year in which the cumulative cash flow equals or exceeds I_0. The probability of success is estimated as the proportion of iterations with a positive NPV, $P(NPV > 0) \approx (1/N)\,\Sigma_i\, 1\{NPV_i > 0\}$.

D. Open data architecture and APIs for calibration.

The model does not set macroeconomic parameters arbitrarily; it retrieves them programmatically via the World Bank Indicators API (version 2), using the WDI package in R [38], [41]. Three official indicators for Honduras are retrieved: annual consumer price inflation (FP.CPI.TOTL.ZG), personal remittances received as a percentage of GDP (BX.TRF.PWKR.DT.GD.ZS), and real GDP growth (NY.GDP.MKTP.KD.ZG). The remittance data is compared with the annual report of the Central Bank of Honduras [18].

The architecture serves three functions: the first is observed inflation, which provides a range of growth in the costs used in the triangular distributions. Second, remittances and GDP growth calibrate the migration/remittance factor, which scales with diaspora demand. Third, and most significantly, automation via APIs transforms the simulation into a dynamic tool by re-running the workflow with a reproducibility seed; the model will automatically incorporate the most recent published figures and ensure traceability and auditability. This integration of advanced analytics and open data is the operational expression of digital transformation in SMEs [39], [40], which distinguishes the model from a static spreadsheet, which is prone to becoming obsolete with each decision-making cycle.

E. Metamodel Calibration and Evaluation Protocol

The 10,000 synthetic scenarios are randomly divided into two subsets: 70 % for training (7,000 scenarios) and 30 % for testing (3,000 scenarios). All reported metrics correspond to the test set rather than the training set, avoiding the optimistic bias associated with in-sample evaluation.

The hyperparameters are fixed a priori and documented in the configuration file accompanying the model. Random Forest uses 500 trees, three candidate variables per split (mtry = 3, close to p/3 for p = 11 predictors), and a minimum node size of five observations. Gradient Boosting uses 800 trees, an interaction depth of 3, a learning rate of 0.05, and 80 % subsampling in each iteration. The combination of a low learning rate and a high number of trees controls overfitting, while depth 3 permits interactions of up to third order.

IV. Model Development

Table 2 shows the financial data used for the Montecarlo simulation data generation. Estimated CAPEX totals L 379,650 and includes the initial trademark registration fee of L 22,000, the minimum 12,000-liter production batch at L 120 per package, labels at USD 0.05 per bottle, certified pallets at L 290 each, and launch, quality-assurance, and contingency expenditures. Profitability therefore depends more on price and sales volume than on fixed capital, directing managerial attention toward commercial variables.

Table 2. Logical-causal flow of the simulation and decision model

Layer	Component	Input/Process	Result
1	Macroeconomic data (API)	Inflation, remittances, GDP	Calibrate costs and demand
2	Operational data	Product, packages, pallets, contract manufacturing	Cost structure
3	Strategic factors	Nostalgic acceptance, migration/remittances, shortage	Adjust demand
4	Monte Carlo simulation	10,000 triangular iterations	Scenario distribution
5	Financial results	NPV, IRR, payback, P(success)	Assess feasibility
6	Machine-learning metamodel	Random Forest and Gradient Boosting	Patterns and importance
7	Decision	Approve/condition/reject	Managerial decision

V. Results

The simulation with 10,000 iterations shows potentially positive returns, but only under controlled conditions. The probability of success, defined as NPV greater than zero, is 69.77 %; approximately seven of every ten scenarios create value, while three destroy it. Table 3 summarizes the

distribution, and Figs. 1 and 2 show the NPV histogram and cumulative probability. Average NPV is L 295,052, mean IRR is 62.66 %, and average payback is 2.07 years. Nevertheless, the negative 5th percentile confirms that approval should not be automatic.

Table 3. Statistical results of the Monte Carlo simulation.

Indicator	Result
CAPEX	L 379,650
Average NPV	L 295,052
Median NPV	L 253,090
Standard deviation of NPV	L 531,613
5th percentile	L −497,870
25th percentile	L −74,550
75th percentile	L 612,656
95th percentile	L 1,232,926
Minimum NPV	L −1,358,491
Maximum NPV	L 2,899,697
Probability of success	69.77 %
Probability of loss	30.23 %
Average IRR	62.66 %
Median IRR	58.37 %
Average payback period	2.07 years
Median payback period	2.00 years

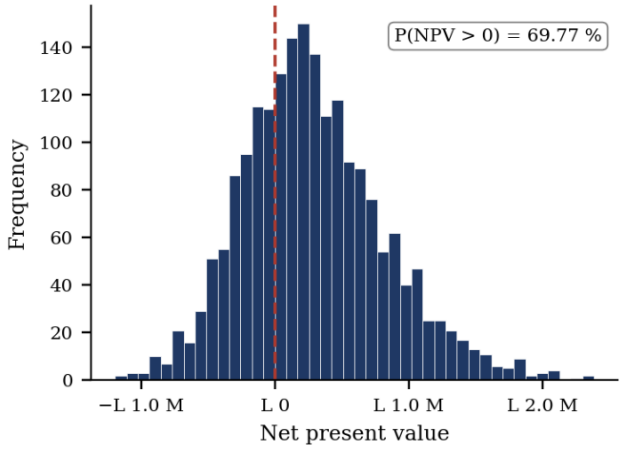


Figure 1. NPV distribution (10,000 iterations). The dashed line indicates the break-even point NPV = 0.

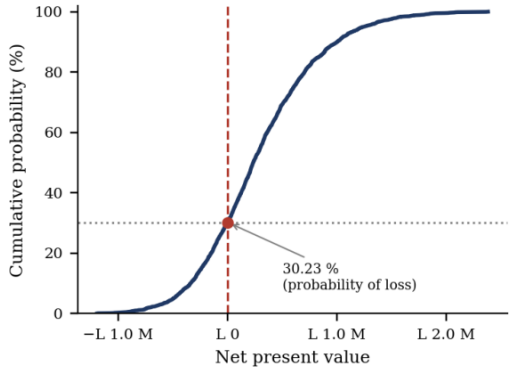


Figure 2. NPV S-curve. The intersection at NPV = 0 reflects the cumulative probability of loss (30.23 %).

A. Comparison with the deterministic scenario

The deterministic scenarios reveal the asymmetry of project outcomes; see Table 4 and Fig. 3. The optimistic scenario multiplies the base NPV several times, whereas the pessimistic and critical-shortage scenarios generate considerable losses. Such asymmetry is typical of projects that are highly sensitive to price and consumer acceptance.

Table 4. Deterministic Scenarios for the Replacement Project

Scenario	NPV	NCF Year 1	NCF Year 5	Result
Pessimistic	L −1,427,901	L −290,563	L −439,574	Loss
Base	L 251,224	L 227,208	L 128,140	Success
Optimistic	L 7,675,830	L 1,938,166	L 2,633,382	Success
Critical shortage	L −828,637	L −51,261	L −280,597	Loss

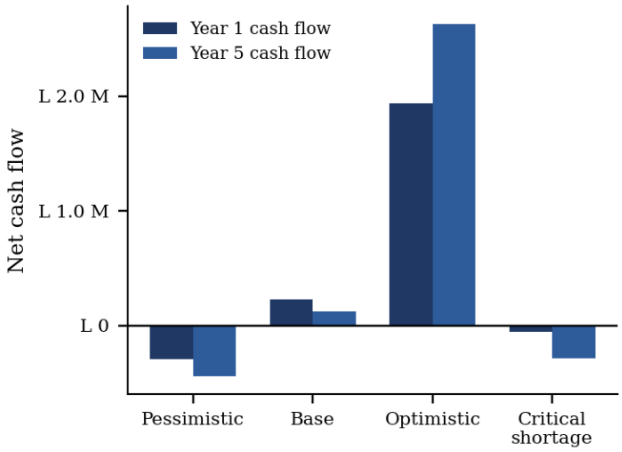


Figure 3. Net cash flows (Year 1 and Year 5) by deterministic scenario

B. Identification of the sensitivity of critical variables.

As shown in Table 5 and Fig. 4, variables are ranked by their Spearman correlation with NPV. Package price leads the ranking ($\rho = 0.771$), followed by initial demand ($\rho = 0.392$) and variable cost ($\rho = -0.380$). This hierarchy reflects a contract-manufacturing model in which profitability depends on the difference between selling price and total package cost. Nostalgic acceptance, shortage opportunity, and migration/remittances show moderate positive associations,

contributing a symbolic and commercial dimension without determining profitability independently [37].

Table 5. Sensitivity of critical variables (Spearman's correlation).

Variable	Spearman ρ	Impact
Package_Price	0.771	High
Demand_Y1	0.392	High
Variable_Cost_Pack	−0.380	High
Manufacturing_Cost	−0.323	Moderate
Logistics_Cost_Pack	−0.185	Moderate
Shortage_Factor	0.171	Moderate
Nostalgia_Factor	0.167	Moderate
Annual_Fixed_Cost	−0.157	Moderate
Migration_Factor	0.154	Low
Cost_Inflation	−0.094	Low
Label_Cost_USD	−0.077	Low

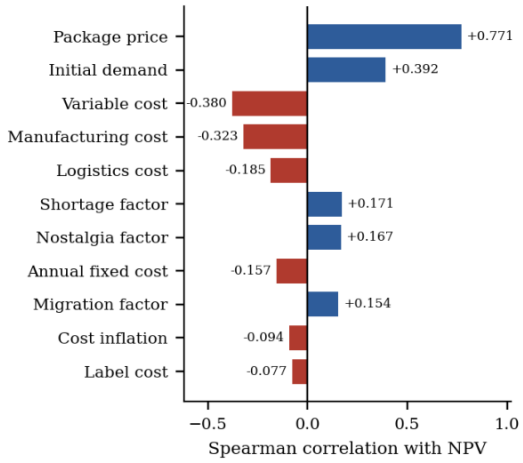


Figure 4. Sensitivity analysis using Spearman's correlation.

C. Comparison with the deterministic scenario

Table 6 reports the test-set performance of the metamodels, while Fig. 5 presents Random Forest variable importance. Gradient Boosting achieves an R^2 of 0.988 for NPV regression and an AUC of 0.997 for success/failure classification. Random Forest achieves an R^2 of 0.951 and a classification accuracy of 95.20 %. These values show that the surrogate models reproduce the simulator's response surface within the sampled domain and identify combinations associated with losses [7], [34]. The leading variables agree with Spearman's ranking—price, demand, and variable cost—although interactions reorder the strategic factors. The two measures should therefore be interpreted jointly [32], [36].

Sensitivity analysis also provides a critical assessment of the positioning. Since price dominates profitability, competing on price would be a mistake. Positioning the product as a cheap knockoff would squeeze the margin and essentially sacrifice authenticity, whereas positioning it as a legitimate nostalgic alternative allows for a price that can absorb manufacturing costs, labeling, logistics, and exchange rate risks. The pessimistic scenario—which combines low acceptance, low price, high costs, and limited opportunity due to supply shortages—results in a significantly negative NPV.

Table 6. Metamodel performance on the test set (30 % of the scenarios).

Model	R^2/AUC	RMSE/Acc.	Type
Random Forest – NPV	0.951	L 121,879	Regression
Gradient Boosting – NPV	0.988	L 60,653	Regression
Random Forest – success	0.991	95.20 %	Classif.
Gradient Boosting – success	0.997	97.37 %	Classif.

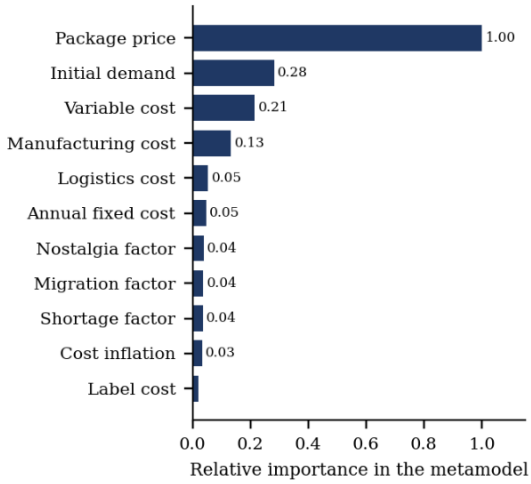


Figure 5. Variable importance (Random Forest) for NPV prediction.

VI. Discussion

A. Investment Decisions Derived from the Model

At the operational level, the recommendation is to proceed in stages. The first step is to produce a minimum batch of 12,000 liters as a controlled commercial trial. Subsequently, actual turnover, consumer acceptance, and net margin should be evaluated. Only if the product maintains the minimum price and the estimated contract volume makes sense should it be scaled up to a permanent business unit. This sequence limits initial exposure and provides market information before committing to larger investments. Therefore, digitalization is evident in the use of open data and monitoring, authenticity, the nostalgia factor, and administrative management regarding investment thresholds, contracts, pricing, and supply.

Table 7 summarizes the managerial decisions derived from the model and their quantitative justification.

Decision	Recommendation	Justification
Approve or reject	Conditional approval	P(success) = 69.77 %; NPV > 0; loss = 30.23 %
Minimum price	Do not sell below L 175–180/package	Most sensitive variable
Minimum volume	At least 4 containers/year or equivalent	Initial demand is the second critical variable
Contract manufacturing	Contract near L 120 with adjustment clause	Variable cost reduces NPV
Nostalgic acceptance	Validate packaging, brand, and flavor	Affects demand and NPV
Shortage response	Complement first, then scale as a unit	Reduces rejection and portfolio risk
Monitoring	Update the model through the API quarterly	Converts simulation into control

B. Limitations

Consequently, several limitations must be acknowledged, as this demand is based on a strategic assumption rather than on historical data for the new product, which is not yet in operation. The price was modeled as a triangular variable and will be replaced by actual data once a commercial policy is defined. The nostalgic acceptance factor requires empirical validation through surveys or market tests.

A suitable design would combine a blind sensory test, in which consumers compare the substitute against the original without brand cues, with a choice-based conjoint survey administered to two samples: domestic consumers and Honduran diaspora households in the United States. The former isolates product acceptance from brand recognition, while the latter estimates willingness to pay and calibrates the migration factor. A limited regional pilot launch would then provide the sell-through data needed to replace the assumed triangular range with observed values.

The model assumes independence among the thirteen stochastic variables, and two pairs deserve particular attention. First, selling price and initial demand are likely to be negatively correlated, since a higher price tends to reduce the quantity sold; treating them as independent allows the sampler to draw scenarios in which both are simultaneously favorable, which plausibly inflates the reported probability of success. Second, contract-manufacturing cost and cost inflation are mechanically related, as both respond to the same input-price pressures; their independent treatment understates the joint severity of adverse cost scenarios. Both biases point in the same direction, namely toward an optimistic estimate, which reinforces rather than weakens the conditional nature of the recommendation. Modeling these dependencies with copulas is the natural next step.

Furthermore, regulatory risks related to labeling and health permits are not incorporated. None of these restrictions invalidates the exercise, as the purpose is not to predict with certainty but to support decision-making under conditions of uncertainty through a transparent and replicable procedure.

VII. Conclusions

This article developed a Monte Carlo simulation and machine-learning metamodel supported by open data retrieved through APIs. The simulated evidence indicates potential viability, with a positive average NPV, a mean IRR above the cost of capital, and an average payback period of 2.07 years. However, the 69.77 % probability of success supports conditional approval rather than an automatic decision. The integrated framework simultaneously quantifies profitability, loss risk, sensitivity to critical variables, nostalgic acceptance, and the opportunity created by shortage conditions, converting uncertainty into actionable managerial criteria. The analysis does not replace managerial judgment; it makes that judgment transparent and defensible. Theoretically, the study integrates financial analysis, brand authenticity, and portfolio resilience in a single decision framework. Methodologically, it combines simulation, metamodeling, and a reproducible open-data layer as a concrete expression of digital transformation in an SME. Practically, it specifies minimum price, volume, contract-manufacturing, and scaling criteria. Future work should validate nostalgic acceptance through diaspora surveys, incorporate observed turnover data, model dependence among variables using copulas, and extend the framework to other nostalgic products and markets.

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