A Data Driven Approach for Decision Making in Food Combo Offer

RETL407 - Final Report

Kaibo Zhang

kaibo.zhang@mail.mcgill.ca

Yanfei Wu

yanfei.wu@mail.mcgill.ca

Mingshu Liu

mingshu.liu@mail.mcgill.ca

David Min

chanhee.min@mail.mcgill.ca

Charlie Tomlinson

charles.tomlinson@mail.mcgill.ca

April 21, 2025

Abstract

Using internal point-of-sale data and external survey feedback, this study proposes a unified framework for optimizing food combos in the convenience retail context. (a) We develop a predictive demand model that incorporates lagged price effects, cross-product interactions, and seasonality, enabling accurate estimation of price-response behavior. (b) We then implement a linear programming formulation to identify combos that jointly maximize margin and consumer affinity under operational constraints. (c) Empirical validation through Net Promoter Score (NPS) analysis and NLP-based feedback review reveals that consumers prefer smaller, nutritionally balanced combos aligned with their spending expectations and prior behavior. The proposed methodology outperforms legacy offers and uncovers key behavioral segments—such as vegetarians and price-sensitive shoppers—that shape adoption likelihood. Our findings underscore the value of integrating behavioral modeling, optimization, and external validation to improve bundle design and decision-making in retail operations.

1 Introduction

In today's competitive convenience retail environment, product relevance and pricing precision have become central to driving consumer engagement and profitability. As customer expectations evolve rapidly across regions, multi-item promotions, such as food combo offers, must be not only operationally feasible but also behaviorally aligned. Couche-Tard, a leading player in Quebec's retail landscape, has invested heavily in expanding its fresh food offerings; however, current combos, often adapted from international formats, have shown limited traction in the local market. This disconnect raises a broader managerial challenge: how can convenience retailers use internal behavioral data to design and evaluate offers that resonate with time-constrained consumers while sustaining margins? In this study, we present a data-driven framework that leverages point-of-sale transactions, demand modeling, and optimization techniques to identify high-potential combo configurations. We further validate our recommendations through survey-based stated preference data, offering Couche-Tard an integrated decision-support system for next-generation food bundle design.

2 Company Overview

Alimentation Couche-Tard Inc., based in Laval, Quebec, stands as one of the leading global operators in the convenience store industry. Established in 1980 by Alain Bouchard, the company has expanded from a single location into a multinational enterprise encompassing approximately 14,500 stores across more than 25 countries and territories, employing nearly 149,000 individuals worldwide [1]. The firm operates under multiple retail banners, most notably Couche-Tard, Circle K, and On the Run. While Circle K serves as the company's principal international brand, the Couche-Tard name remains predominantly used within Quebec, underscoring the company's regional roots and strong market presence. Within the province, Couche-Tard manages a total of 1,426 locations, affirming its status as a dominant player in the Quebec retail landscape.

3 Problem Statement and Objectives

Our study is motivated by persistent underperformance in Couche-Tard's food combo offerings, particularly within the Quebec market. Although the company has invested heavily in enhancing its food proposition, the current set of combo deals—largely adapted from U.S. consumer patterns—has failed to generate meaningful engagement among Quebec customers. This suggests a misalignment between product design and local consumer expectations. The central problem addressed in this project concerns the challenge of designing combo offers that not only reflect regional preferences but also support sustainable profitability in a convenience retail context.

This work is designed to support Couche-Tard in improving the performance of its food combo offerings by generating data-driven, operationally feasible recommendations in multi-item promotional settings. Specifically, we explore how customers respond to various item and food combinations when presented as bundles. While prior research has focused on single-item price elasticity and category-level brand performance [2], we extend this work by evaluating consumer acceptance of mixed-brand combos (i.e., private/national) using both revealed (sales) and stated (survey) preferences. Our second focus is on bundle design: using high-frequency point-of-sale data, we analyze co-purchasing behavior to uncover natural product affinities. This informs the identification of combinations that are both behaviorally aligned and commercially viable. Due to data limitations and implementation goals, the analysis intentionally excludes benchmarking against competitor promotions. Lastly, the project incorporates a pricing lens, assessing combo appeal based on its influence on uptake and profitability. Rather than pursuing short-term volume gains, we emphasize pricing strategies that align with consumer value perceptions, drawing from transaction records and survey responses. The project remains grounded in feasibility, aiming to deliver insights that are both analytically robust and operationally actionable.

4 Data Description

The data used in this project were obtained directly from Couche-Tard's internal systems and consist entirely of proprietary records. The primary dataset is a comprehensive collection of point-of-sale (POS) transaction data extracted from the company's centralized database. These records span the period from January 1, 2021, to February 12, 2025, and are stored in individual files by transaction date. Each POS record includes detailed information such as transaction timestamps, product names, unit prices, quantities sold, and associated site location identifiers. This structure enables high-resolution tracking of purchase behavior across time and geography, supporting analyses of price elasticity, market basket patterns, and temporal sales trends. In addition to transactional data, the dataset includes product-level metadata that captures attributes relevant to brand strategy and margin analysis. These include procurement cost, brand classification (i.e., national vs. private label), manufacturer identity, and internal affinity scores measuring the likelihood of co-purchase. Site-level metadata, such as regional identifiers and store format, are also available and can be linked to each transaction to enable geographic segmentation. To supplement behavioral data, a structured consumer survey was conducted via the Proliphic platform, targeting Canada-based respondents. The survey collected stated preference data regarding newly proposed combo configurations and yielded 404 valid responses. These survey results serve as a complementary data source, allowing validation of purchasing patterns observed in the POS data with direct consumer sentiment. Together, these datasets form the empirical foundation for the project's pricing, bundling, and brand preference analyses.

5 Methodology

5.1 Overview

This project follows a multi-stage methodology to develop optimized food combo offers for Couche-Tard's Quebec market (Figure 1). It begins with transaction-level analysis to identify frequent purchasing patterns using POS data. These insights inform a forecasting model that estimates demand sensitivity through price elasticity regressions. A linear programming model then generates optimal combo configurations under key operational constraints, including category limits and supplier rules. Collectively, this approach combines behavioral insights, predictive modeling, and optimization to guide data-driven promotional decisions.

5.2 Association Rule Mining (Apriori)

A key preliminary step in the development of effective combo offerings is the identification of product combinations that reflect actual consumer behavior. With over 5,000 distinct items in Couche-Tard's assortment, the full combinatorial search space is prohibitively large—both computationally and operationally. Moreover, offering promotions on low-traffic or niche products would yield limited business value. Therefore, it was necessary to strategically reduce the search space by isolating top-selling items that are both relevant to customers and impactful to overall sales performance. We analyzed POS from 215 stores across Quebec, covering a 31-day period in January 2025. Using association rule mining, we first filtered for products that were frequently purchased on their own, then examined which of these items tended to appear together in the same transaction. A minimum threshold was applied such that only products appearing in at least 1% of transactions were considered. This ensured a focus on widely relevant items while excluding infrequently purchased products from consideration.

The results reinforced a core aspect of Couche-Tard's identity as a quick-stop, convenience-driven store. Most customers enter with the intent to make rapid, task-oriented purchases: often on the way to work, during a commute, or between errands. As such, their shopping behavior is shaped by time constraints, limited carrying capacity, and the absence of planned basket purchases. The predominance of single-item transactions observed in the data confirms this consumer mindset, where immediacy and simplicity outweigh the incentives to browse or build larger baskets. While strong multi-item baskets were rare, we successfully identified 39 top-selling drinks and snacks and 37 high-performing food items, all of which ranked in the top 5% of sales (Table 3). These products already resonate with consumers and can serve as credible anchors for combo offers—ones that enhance convenience rather than complicate it. By limiting the analysis to this high-impact subset, we reduced the otherwise prohibitive complexity of evaluating all possible combinations and ensured that subsequent modeling efforts remained computationally efficient and commercially relevant.

5.3 Modelling the Demand Function

To support pricing and bundling decisions with quantitative evidence, we developed a predictive demand model that captures product-level responsiveness to price changes and substitution effects. The goal was to estimate how demand for each item evolves over time and responds to its price history, the prices of related products, and broader seasonal dynamics. This enables Couche-Tard to simulate expected sales under alternative pricing and combo configurations. The demand for product i on day t is modeled as:

$$Q_{it} = const_i{}^1 + \sum_{k=0}^{3} \beta_{1k} P_{i,t-k}{}^2 + \sum_{j \in \mathrm{Cor}_{\geq 0.6}} \beta_j \cdot P_{j,t}{}^3 + \gamma_t{}^4 + \epsilon_{it}{}^5$$

This structure allows the model to reflect several realistic elements of consumer behavior in a convenience retail setting. First, the inclusion of lagged prices from today to three days prior accounts for short-term memory and habitual shopping behavior. Customers in Couche-Tard stores often shop on the go and may remember a product being on sale earlier in the week, which can influence their decision even after the discount ends. The 3-day window is also operationally meaningful, aligning with common promotional cycles and consumer attention spans. Incorporating cross-price effects allows the model to reflect how price changes in substitutes or complementary items influence the demand for a focal product. For instance, if a competing energy drink (e.g., Monster) is discounted, demand for Red Bull may fall; similarly, if a pastry item commonly paired with coffee rises in price, it may affect the total demand for the combo. These dynamics are especially relevant for a store format that serves time-constrained customers making fast but interrelated decisions. Seasonal and temporal effects, such as weekday/weekend cycles and monthly trends, are captured by γ_t, which was estimated using NeuralProphet [3], a time-series pre-trained neural network well-suited for identifying non-linear patterns from the residuals after initial regression. This adjustment ensures that the model reflects not just price sensitivity but also predictable

[1] $const_i$: Item-specific baseline demand for product i.

[2] $P_{i,t-k}$: Price of product i on day $t-k$, with $k = 0, 1, 2, 3$, capturing price memory.

[3] $\sum_{j \in \mathrm{Cor}_{\geq 0.6}} \beta_j \cdot P_{j,t}$: Cross-price effects from products with a sales correlation ≥ 0.6 with product i.

[4] γ_t: Time adjustment term capturing seasonality and time trends, estimated using NeuralProphet.

[5] ϵ_{it}: Random error term accounting for unexplained variation.

variation in traffic and purchasing behavior tied to time. Overall, this demand function provided a strong foundation for downstream pricing simulations.

The model demonstrates reasonable predictive accuracy in the test set, with an average RMSE of 247.27, indicating that, on average, the predicted daily sales deviate from actual sales by roughly 247 units. In the context of daily transaction volumes exceeding 1,000 units for many products, this level of error is considered acceptable for informing pricing and promotion strategies. From figure 2, it is clear that the model closely follows the general shape and timing of sales fluctuations, particularly in capturing the low-end troughs and weekly cyclicality. However, it underestimates the magnitude of sharp sales spikes, indicating a limitation in capturing extreme demand surges. Despite this, the model remains highly valuable in this study's context, where operational planning benefits more from reliable baseline and trend forecasting than from anticipating rare peak values. Its ability to replicate the pattern and rhythm of real sales ensures informed, data-driven pricing and inventory decisions.

5.4 Linear Programming for Optimal Food Combo

To translate consumer preferences and product performance into actionable bundle offers, we developed an optimization framework using linear programming (Appendix 9). The central rationale for this approach lies in its ability to simultaneously address two critical business goals: maximizing expected profit and maintaining consumer relevance. In the context of Couche-Tard's retail environment, where space, pricing flexibility, and consumer attention are all limited, manually balancing these priorities across thousands of product combinations would be infeasible. A structured model enables consistent, scalable, and data-driven decision-making.

The model's objective function is designed to jointly consider margin and bundle coherence. This is achieved by assigning a weight (α=0.6), determined in consultation with Couche-Tard professionals, to reflect the company's belief in the relative importance of profit versus consumer relevance. The logic behind this formulation is twofold. First, products with high historical sales volumes signal strong consumer willingness to pay and a higher likelihood of being purchased again when included in a combo. Second, pairing items that exhibit strong correlations in their daily sales, especially relative to a selected food anchor, helps ensure that the resulting bundle mirrors existing shopping behavior. In essence, if two items consistently move together in sales, they are more likely to appeal to the same consumer and not violate their implicit buying logic. This avoids producing incoherent combos that consumers are unlikely to find relevant or attractive. The algorithm also incorporates several real-world constraints that mirror operational requirements. These include rules ensuring category exclusivity (C4, no duplicate categories per bundle), nutritional balance (C5 and C6, each bundle must contain one food item and no more than two beverages), and supplier considerations (C9, preventing competing manufacturers from appearing together). To qualify as a promotional offer, at least one product in each combo must also be discounted. This structured logic ensures that every recommended bundle can be feasible in-store without violating merchandising or supplier guidelines.

The output of this optimization process produced a shortlist of high-potential combos featuring products such as steak paninis, fruit and cheese boxes, muffins, and popular beverages like Red Bull and Pepsi (Table 4). These options align closely with observed preferences in the Quebec market, and they meet both nutritional and promotional criteria. Importantly, the structure enables Couche-Tard to continuously refresh combo offerings based on updated sales and demand inputs, making the system scalable for future promotional cycles. Ultimately, the LP model not only delivered a targeted set of viable and profitable combos but also provided a replicable framework for data-driven promotion planning within a constrained retail environment.

6 Price Elasticity Analysis

To assess consumer responsiveness to brand type and support the outputs of the optimization model, a category-level price elasticity analysis was conducted, focusing on private-label versus national-brand products (Appendix 9). The elasticity estimates, presented in Table 2, are derived from a log-log specification, allowing direct interpretation as percentage effects: for example, a coefficient of –0.1 indicates that a 1% decrease in price results in a 0.1% increase in quantity sold, holding temporal effects constant. Overall, minimal variation was observed between brand types within most categories; however, notable differences emerged in the soft drink and candy segments, where private-label products exhibited slightly positive elasticity values. This counterintuitive result likely reflects low price variability over time and a general insensitivity to price in these categories. While not conclusive evidence of preference for national brands, the observed differences may signal stronger brand loyalty or baseline demand for those products. More broadly, non-perishable snack and beverage categories exhibited greater price sensitivity, with national-brand energy drinks showing the highest elasticity across all segments. Some lunch-related non-perishable items also appeared price-sensitive, though corresponding brand label mappings were unavailable, limiting their inclusion in the final analysis. For Couche-Tard, these results suggest that price promotions on branded energy drinks or snacks are likely to yield more measurable volume lift, whereas promotions on private-label items in certain categories may have limited impact. Additionally, the observed loyalty to national brands in impulse categories highlights an opportunity to selectively position private-label alternatives more strategically to capture margin without undermining consumer trust.

7 External Validation

7.1 Survey Setup and Deployment

To complement the internal data analysis and validate model-driven combo recommendations, an external survey[1] was conducted via Prolific as part of the experimental design. The rationale for deploying a survey was to assess how real consumers would react to proposed bundles in a controlled setting, especially since transaction-level data alone cannot capture intention, perceived value, or emotional response. This external validation step strengthens the reliability of insights derived from sales and optimization models, offering a behavioral checkpoint grounded in consumer feedback. Respondents were first shown a simulated shelf containing both items in the proposed combos and related products, each with their respective retail prices. They were asked to first create a desired shopping list as if shopping in-store and then rate each combo individually on a scale from 0 to 10, where 0 indicated

[1]Survey form: `https://www.surveyhero.com/c/qxay7djr`
Response dataset: `https://docs.google.com/spreadsheets/d/1B9mIIjcnr4RrJltPV2_Dz8SZpHzwEat4/edit?usp=sharing&ouid=102765056920996051257&rtpof=true&sd=true`

no interest and 10 indicated a strong preference to purchase the combo instead of their original selections. A control group was included, featuring a previously released combo from 2019, allowing for comparative benchmarking of newer combos against historical offerings. By combining stated preferences with revealed behaviors, the survey adds interpretive depth, highlights gaps in current offerings, and informs product design with forward-looking customer sentiment.

7.2 Net Promoter Score Analysis

To evaluate consumer interest in proposed combo offers, we employed the Net Promoter Score (NPS) framework—a benchmark widely used in retail to measure customer sentiment and likelihood of adoption. NPS is calculated by subtracting the percentage of detractors (respondents rating a combo 0–6) from the percentage of promoters (ratings 9–10). Scores can range from −100 to +100, with higher values indicating stronger customer enthusiasm.

Among all six tested combos[2], performance varied substantially (Figure 3). The best-performing bundle was Combo 3, which received an NPS of –27.47. Although still negative, this score represents a meaningful improvement over all other test and legacy bundles. The control group Combo 2 received a moderately negative score of –32.43. While better than some newly tested offers, the control combo's relatively low appeal suggests a disconnect between legacy pricing strategies and current consumer preferences. This is particularly relevant given that the control includes well-known national brands and a full beverage pairing, indicating that recognition alone is not sufficient to drive perceived value. Combo 4 performed significantly worse than its simpler counterpart, receiving an NPS of –66.58. This highlights the risk of over-bundling: while each individual item may perform well on its own, including a high-cost item like Red Bull can tip the combo beyond an acceptable price range in the eyes of the consumer. Combo 1 yielded a score of –43.31. Though underwhelming

[2] Combo configurations:
Combo 1: Muffin morceaux chocolat & Grill Hot Dog;
Combo 2 (Control): Baguettine au jambon, Lay's Classic 77g, Pepsi 6101ml, Eska 600ml;
Combo 3: Collation fruits et fromage, Panini au steak;
Combo 4: Collation fruits et fromage, Panini au steak, Red Bull 250ml;
Combo 5: Baguettine au jambon, Chocolatine, Red Bull 260ml, Pepsi 6101ml or CK/CT Eau Source 600ml;
Combo 6: Muffin morceaux chocolat, Grill Hot Dog, Red Bull sans sucre 260ml, TSB remplissage café.

overall, it still outperformed Combo 6, a similar composition with added drink components, which received the lowest NPS. The steep decline between the two confirms that simply increasing the combo size does not equate to increased appeal. In fact, when combos appear too large or too mismatched, consumers may reject them outright. This finding is especially critical for Couche-Tard, given its positioning as a quick-stop, low-friction convenience store. Consumers walking into a Couche-Tard are unlikely to seek large, high-commitment meal bundles and are particularly sensitive to overstuffed offers that appear either excessive or expensive.

Price expectations were a central driver of NPS variation (Figure 4). Most respondents indicated an anticipated spend between \$5 and \$15, and NPS values tended to peak when combos fell closer to the lower bound of this range. Notably, Combo 3 was viewed more favorably even among consumers expecting to spend less than \$10, despite being composed of two fresh items. This suggests that combos perceived as high-quality or "balanced" may justify a moderate price point if they align with perceived value. On the other hand, combos including energy drinks, multiple beverages, or redundant components performed poorly across all spending segments, implying that these inclusions are not seen as additive, but rather as price inflators. Measured by whether a respondent had previously selected one or more items in the combo during the shopping simulation, the level of engagement also had a significant impact on NPS (Figure 5). Highly engaged respondents gave consistently higher ratings to combos containing familiar or preselected items. Combo 3, which closely aligns with common pre-basket selections observed in both the survey and POS data, achieved its highest NPS scores among this group. This reinforces the value of behavioral alignment in combo design: when a combo resembles what the consumer was already likely to buy, it feels intuitive and frictionless. In contrast, Combo 6, despite offering more items, scored poorly across both engaged and unengaged segments—suggesting that misalignment in category or pricing can outweigh any potential appeal from perceived abundance.

Finally, the interaction between dietary preferences and engagement behavior revealed a notable satisfaction gap among vegetarian consumers. Across nearly all engagement levels, respondents who identified as vegetarians reported consistently lower NPS scores compared to their non-vegetarian counterparts (Figure 6). This pattern suggests that current bundle offerings may lack sufficient appeal for this segment, particularly for less-engaged consumers who are not already predisposed to the proposed products. Interestingly, the Fruit Box + Panini combo, though not explicitly designed as vegetarian, received relatively stronger ratings from vegetarian respondents, indicating that balanced, plant-forward options have cross-cutting appeal. Moving forward, Couche-Tard could benefit from introducing more intentionally designed vegetarian combos to close this satisfaction gap, improve perceived inclusivity, and boost adoption rates among health- and sustainability-conscious shoppers. Integrating dietary segmentation into combo design could enhance both engagement and consumer loyalty, particularly in urban markets where demands for such options is growing.

7.3 Comments Text Analysis and Limitations

To further understand the drivers behind low combo ratings, we applied natural language processing (NLP) techniques to clean and analyze open-ended comments provided by respondents who gave low scores (i.e., ≤ 3). The qualitative insights revealed a recurring emphasis on maintaining a healthy diet, with several negative sentiments directed toward energy drinks, particularly due to their high sugar content (Figure 7). Additionally, a notable portion of the sample identified as vegetarian, and their feedback suggests that limited plant-based options contributed to dissatisfaction. These findings reinforce the influence of health-conscious and dietary-specific preferences on consumer evaluations and highlight the importance of incorporating nutritional considerations into future combo designs.

While the survey yielded valuable insights, several limitations should be acknowledged. The filtering options available on the Proliphic platform ensured that respondents were residents of Canada; however, more granular demographic data at the provincial level was unavailable due to voluntary disclosure and anonymity constraints. As a result, the representativeness of the sample for Couche-Tard's Quebec customer base could not be fully verified. Additionally, the overall distribution of responses was skewed toward lower ratings, potentially reflecting a more critical subset of consumers. This suggests that NPS results should be interpreted with caution, focusing on relative differences across combos rather than absolute performance. Future iterations would benefit from more targeted sampling and expanded demographic profiling to better align survey participants with target consumers.

8 Recommendation

Based on the results of the optimization model, Net Promoter Score (NPS) feedback, and consumer sentiment analysis, we recommend Couche-Tard implement two refined food combo offers that align with operational feasibility and observed consumer behavior (Figure 8). The primary recommendation is a two-item "Balanced Combo" consisting of a *Fruit and Cheese Snack Box* paired with a sandwich of choice—either the *Panini au Steak* or a vegetarian alternative currently available in Couche-Tard stores. This base combo is priced at \$11.59, a value point selected by the optimization model to balance perceived affordability with profitability, and which falls within the \$5–\$15 range preferred by most survey respondents. If Couche-Tard identifies a strategic need to offer three-item bundles, an extended version of the combo can be introduced by adding a beverage—either a Red Bull or a Pepsi product of the customer's choice—bringing the total price to \$14.71. This revised structure maintains product coherence while offering greater flexibility in consumer choice. The additional beverage was selected not only for its popularity in co-purchase patterns but also for its contribution to basket value when paired with a promotional discount. The composition of these bundles reflects common lunchtime consumption needs. The sandwich component satisfies the customer's need for protein and satiety, while the fruit and cheese box introduces a balanced, health-oriented element that supports a nutritious diet. In the extended combo, the beverage addition addresses thirst and refreshment, completing the meal in a practical and appealing format. This structure supports Couche-Tard's goal of offering nutritionally coherent, on-the-go meals that cater to a diverse range of preferences within a compact and operationally manageable offer.

To maximize the impact of the recommended combo offers, we propose an advertisement strategy that emphasizes price saliency and value transparency. As illustrated in Figure 9, making the discount on price-sensitive items (e.g., beverages) explicit within the bundle framing enhances perceived savings and strengthens consumer purchase intent. Instead of presenting the bundle as a flat price, highlighting the promotional discount on a specific item such as Red Bull or Pepsi reinforces the psychological value of the offer without altering the overall pricing structure. This framing leverages consumer attention to price anchors and aligns with findings from the elasticity and NPS analyses.

Notably, the analysis strongly discourages the use of four-item combos. Empirical findings show that consumer interest and perceived bundle coherence decline significantly beyond three items. In the context of Couche-Tard's quick-service environment, this is likely due to the operational nature of convenience retail: customers are typically time-constrained, carry limited items, and tend to avoid large, complex bundles. Thus, maintaining simplicity in offer structure is essential to securing adoption without increasing friction at the point of sale. Together, these recommendations reflect a synthesis of behavioral insight, pricing optimization, and operational fit. They allow Couche-Tard to move toward modular, data-driven promotions that satisfy both functional lunch needs and evolving consumer expectations, while preserving the core strengths of convenience retailing: speed, simplicity, and value.

9 Discussion and Conclusion

This study introduces an end-to-end data-driven framework to enhance Couche-Tard's food combo offerings in the Quebec market by integrating POS analysis, predictive modeling, and optimization. We identified product pairings rooted in habitual co-purchase behavior, estimated price sensitivity through a model incorporating lagged and cross-product effects, and generated feasible bundle configurations using a linear program constrained by operational realities. Validation through survey-based NPS analysis and text mining confirms that engagement peaks when combos are simple, nutritionally balanced, and priced within the \$5–\$15 range. Notably, two- and three-item bundles anchored by a fruit and cheese box and a sandwich outperformed larger configurations, which proved misaligned with Couche-Tard's quick-stop format. It is important to emphasize that the recommendations are tailored for deployment between April and October 2025, the time horizon set during demand modeling. For periods beyond this window, the full pipeline can be re-executed using more recent transaction data to generate updated forecasts and promotional strategies. Additionally, A/B testing at selected store locations may serve as a cost-effective alternative to survey-based validation, enabling real-time feedback and continuous improvement. Taken together, the proposed methodology offers a replicable and adaptive decision-support system, linking behavioral insights to targeted, high-impact promotional design in convenience retail.

Appendix A: Bundle Optimization IP Model

This model is an extension of the Integer Programming (IP) approximation of the Promotion Optimization Problem (POP[2]). Building on the framework, we computed the unilateral profit across a price vector of length k, where the first entry represents the regular retail price. Each subsequent price level in the vector is derived by multiplying the previous price by 0.98, simulating small markdown steps. The process continues until the discounted price falls below the procurement cost, ensuring all candidate prices remain financially viable. This pre-processing step enables the model to evaluate feasible promotional prices for each product and integrate them into the bundle-level optimization framework.

Sets and Indices:

$\mathcal{I}$	Set of products, indexed by i
$\mathcal{T}$	Set of time periods, indexed by t
$\mathcal{K}_i$	Set of price levels for product i, indexed by k
$\mathcal{P} \subseteq \mathcal{I} \times \mathcal{I}$	Valid product pairs (i, j) with $i < j$
$\mathcal{C}$	Set of product categories, indexed by c
$\mathcal{M}$	Set of disallowed manufacturer pairs (m_1, m_2)

Parameters:

$b_{i,t,k}$	Expected profit of product i at time t and price level k
$\text{Corr}_{i,j}$	Correlation between product i and j
Food_i, Beverage_i	Indicator if i is a food or beverage item
$\text{Cat}_{i,c}$	1 if product i belongs to category c
Manuf_i	Manufacturer of product i
$\alpha \in [0, 1]$	Trade-off weight between profit and bundle coherence
$\underline{B}, \overline{B}$	Minimum and maximum bundle size
C	Normalization constant for unit alignment

Decision Variables:

$\Gamma_{i,t,k} \in \{0, 1\}$	1 if product i is priced at level k at time t
$\text{Included}_{i,t} \in \{0, 1\}$	1 if product i is included in a bundle at time t
$\text{Bundle}_t \in \{0, 1\}$	1 if a bundle is active at time t
$\text{Pair}_{i,j,t} \in \{0, 1\}$	1 if products i and j are bundled together at time t

Objective Function:

$$\max \left[\alpha \sum_{i,t,k} b_{i,t,k} \cdot \Gamma_{i,t,k} + (1-\alpha) \cdot \mathrm{C} \sum_{(i,j)\in\mathcal{P}} \sum_{t} \mathrm{Corr}_{i,j} \cdot \mathrm{Pair}_{i,j,t} \right]$$

Constraints:

$$\sum_{k} \Gamma_{i,t,k} \le 1 \quad \forall i,t \tag{C1}$$

$$\Gamma_{i,t,k} \le \mathrm{Included}_{i,t} \quad \forall i,t,k \tag{C2}$$

$$\mathrm{Included}_{i,t} \le \sum_{k} \Gamma_{i,t,k} \quad \forall i,t \tag{C3}$$

$$\sum_{i:\mathrm{Cat}_{i,c}=1} \mathrm{Included}_{i,t} \le \mathrm{Bundle}_t \quad \forall c,t \tag{C4}$$

$$\sum_{i} \mathrm{Food}_i \cdot \mathrm{Included}_{i,t} = \mathrm{Bundle}_t \quad \forall t \tag{C5}$$

$$\sum_{i} \mathrm{Beverage}_i \cdot \mathrm{Included}_{i,t} \le 2 \cdot \mathrm{Bundle}_t \quad \forall t \tag{C6}$$

$$\underline{B} \cdot \mathrm{Bundle}_t \le \sum_{i} \mathrm{Included}_{i,t} \le \overline{B} \cdot \mathrm{Bundle}_t \quad \forall t \tag{C7}$$

$$\mathrm{Included}_{i,t} \le \mathrm{Bundle}_t \quad \forall i,t \tag{C8}$$

$$\sum_{i:\mathrm{Manuf}_i\in\{m_1,m_2\}} \mathrm{Included}_{i,t} \le \mathrm{Bundle}_t \quad \forall (m_1,m_2),t \tag{C9}$$

$$\sum_{i} \sum_{k\neq 0} \Gamma_{i,t,k} \ge \mathrm{Bundle}_t \quad \forall t \tag{C10}$$

$$\mathrm{Pair}_{i,j,t} \le \mathrm{Included}_{i,t} \quad \forall (i,j),t \tag{C11}$$

$$\mathrm{Pair}_{i,j,t} \le \mathrm{Included}_{j,t} \quad \forall (i,j),t \tag{C12}$$

$$\mathrm{Pair}_{i,j,t} \ge \mathrm{Included}_{i,t} + \mathrm{Included}_{j,t} - 1 \quad \forall (i,j),t \tag{C13}$$

$$\Gamma_{i,t,k}, \mathrm{Included}_{i,t}, \mathrm{Bundle}_t, \mathrm{Pair}_{i,j,t} \in \{0,1\} \tag{C14}$$

Refer to Equation (A1) for the objective function used in the bundle optimization model.

Appendix B: Price Sensitivity Analysis Breakdown

To evaluate consumer price sensitivity across product categories and assess differential responses to private-label versus national brands, we conducted a category-level price elasticity analysis using Couche-Tard's point-of-sale data from 2022 to 2024 in the province of Quebec. The objective of this analysis was threefold: (1) to quantify brand-specific pricing responses, (2) to support the parameters used in the combo optimization model, and (3) to inform future promotional pricing strategies. Products were first filtered to ensure modeling reliability, with inclusion limited to those present in at least 80% of the weeks (i.e., having sales on at least four out of seven days in a given week). Weekly aggregation was then applied to the filtered dataset to smooth volatility while preserving alignment with retail sales cycles.

The elasticity estimation followed a two-stage procedure designed to isolate the effects of pricing from time-driven sales variation. In the first stage, we regressed the log of weekly quantity sold for each product on a set of time fixed effects. The resulting residuals captured demand fluctuations unexplained by temporal patterns. In the second stage, these residuals were regressed on the log of the product's own price and the log prices of its closest substitutes to capture both own- and cross-price elasticities. Product substitutes were identified by constructing a price correlation matrix within each category and selecting the top three products that (i) had a minimum price correlation of 0.2 with the focal product and (ii) maintained an intercorrelation below 0.9 to prevent multicollinearity among competitor prices. The final elasticity estimates for each category-label combination (e.g., national-brand energy drinks) were computed as weighted averages of product-level own-price elasticities, with weights proportional to each product's revenue contribution to its respective category and label group. This weighting approach ensured that elasticity estimates reflected actual sales influence rather than equal product treatment. Collectively, the methodology provides a structured basis for interpreting brand-specific price sensitivity and supports data-driven decision-making in category-level promotional planning.

Model Component	Description
Dependent Variable	Residuals from regressing log(quantity) on time factors
Predictors	Own log(price) and competitor(s) log(price)
Time Factors for Detrending	year, sin(month), cos(month), sin(week), cos(week)
Product Filtering	Present in ≥80% of weeks with weekly presence defined as sales occurring in at least 4 out of 7 days of the week
Competitor Limit	Top three products per correlation strength
Competitor Thresholds	Minimum product correlation of 0.2 with maximum inter-correlation of 0.9 among other competitors
Outlier Removal	Winsorization applied to log price and residuals at 5th–95th percentiles (values capped)
Individual Elasticity Estimates	Coefficient of own log(price)
Category Elasticity Estimates	Sales-weighted average of product-level elasticities

Table 1: Breakdown of Modeling Components

Category	Label	Weighted Elasticity
Boissons Énergétiques (Energy Drinks)	national	-1.64
	private	-1.34
Boissons Gazeuses (Soft Drinks)	national	-0.95
	private	0.03
Eau (Water)	national	-0.67
	private	-0.73
Grignotises Salées (Salty Snacks)	national	-1.58
	private	-1.46
Confiserie (Candy)	national	-1.27
	private	0.24
Grillades (Grill)	national	-0.65
Collations (Snacks)	national	-0.20

Table 2: Category-Level Weighted Elasticities

Appendix C: Graphs and Tables

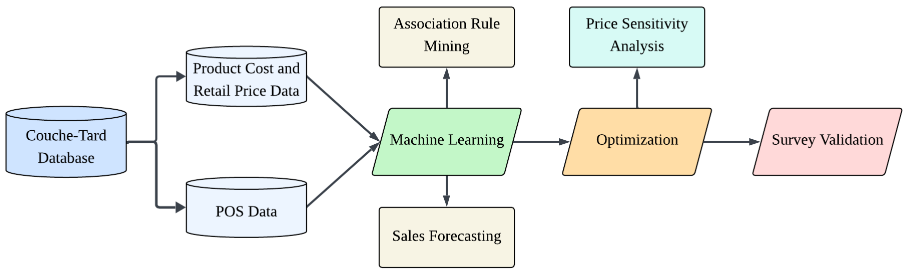

Figure 1: Process Map of Methodology

Support	**Itemset**
0.0862	TSB MOYEN CAFE REGULIER
0.0841	TSB PETIT CAFE REGULIER
0.0644	RED BULL 250ML
0.0433	LACTANTIA LAIT 2% 4L
0.0376	CK/CT LAVE-GLACE -45 3.78L
0.0358	RED BULL 473ML
0.0329	BREUV.FROID FONTAINE 20OZ
0.0301	CSP DANOISE YOG.GREC CERISE

Table 3: Example of Top Frequent Itemsets from POS Data[3]

Combo	**Product**	**Price Level**
Combo #1	HOT DOG	0
	CHOCOLATE CHIP MUFFIN	1
Combo #2	STEAK PANINI	0
	FRUIT AND CHEESE SNACK BOX	1
Combo #3	STEAK PANINI	0
	FRUIT AND CHEESE SNACK BOX	0
	RED BULL (250ML)	11

Table 4: Example Optimized Combo Configurations

[3]Support refers to the proportion of total transactions in which the item appears. For instance, a support value of 0.0862 means the item was purchased in 8.62% of all recorded transactions.

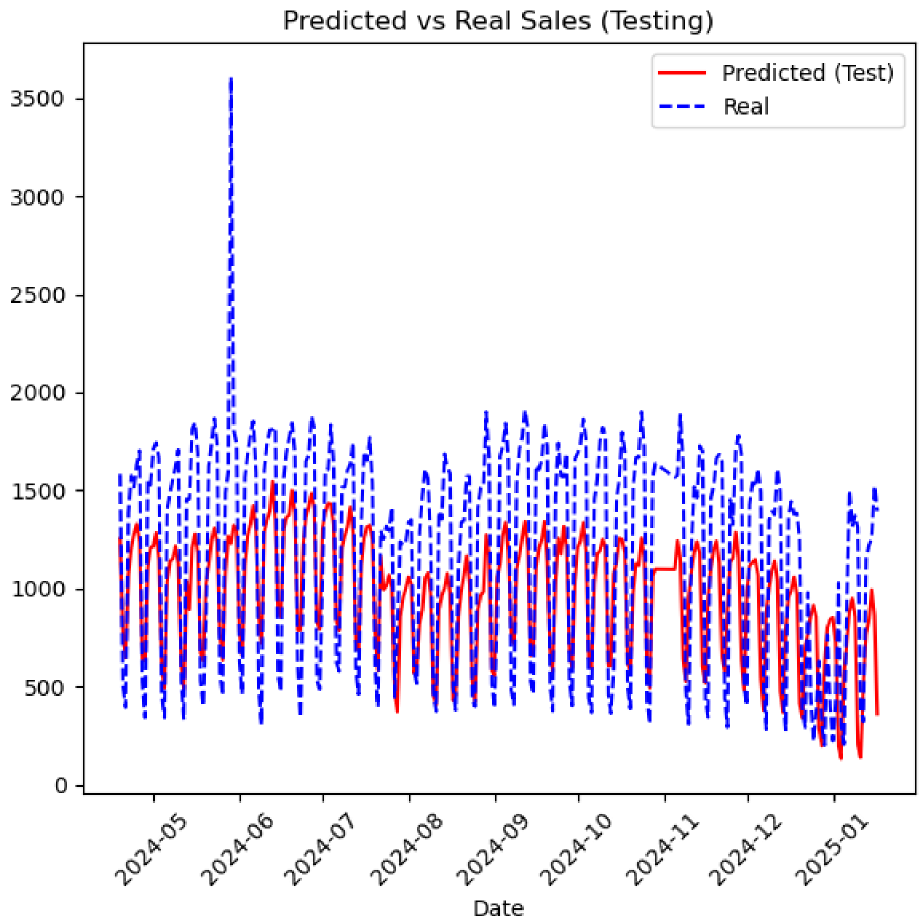

Figure 2: Example Model Test Set Performance

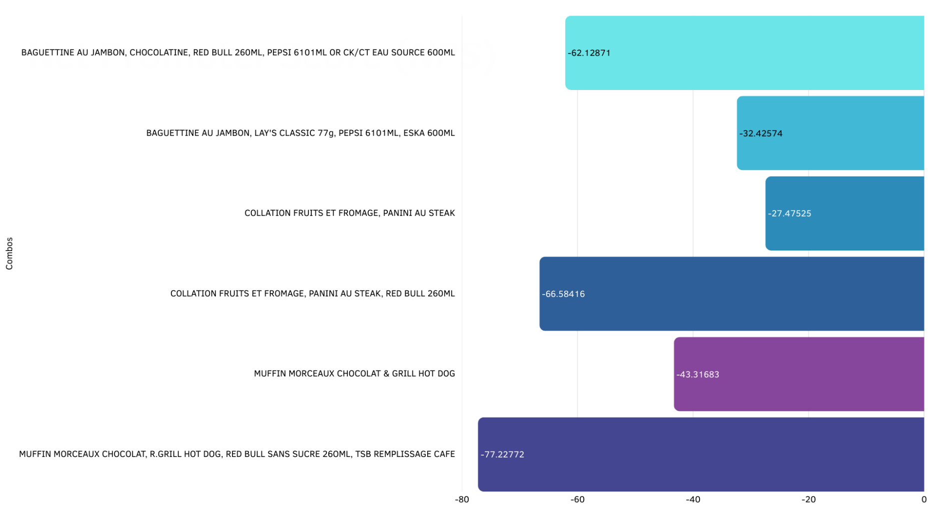

Figure 3: Bar Chart of Combo Offer Overall NPS

Image	Combo Items	Price ($)
	Hot Dog, Chocolate Chip Muffin	4.84
	Baguettine au jambon, Lay's Classic, Pepsi, Eska	12.75
	Fruit and Cheese Snack Box, Steak Panini	11.59
	Fruit and Cheese Snack Box, Steak Panini, Red Bull 250ml	14.71
	Baguettine au jambon, Chocolatine, Red Bull 260ml, Pepsi or Water	15.78
	Chocolate Muffin, Grill Hot Dog, Red Bull (Sugar-Free), Coffee Refill	10.52

Table 5: Combo Deployed in Survey with Visuals, Components, and Pricing

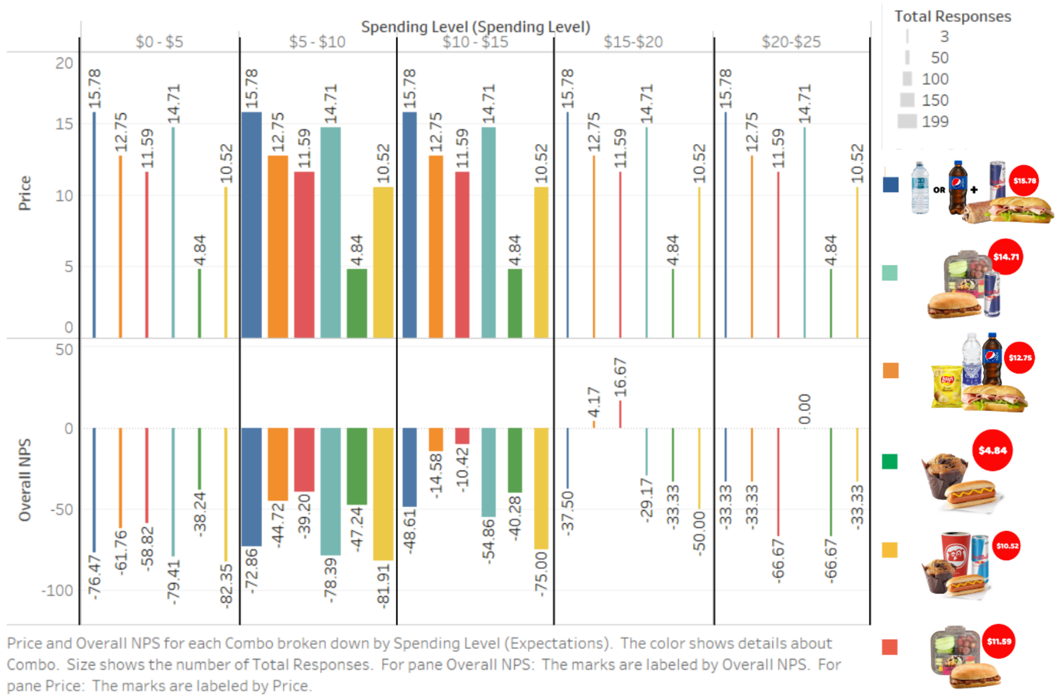

Figure 4: Bar Chart of Combo Offer NPS by Expected Spending Level

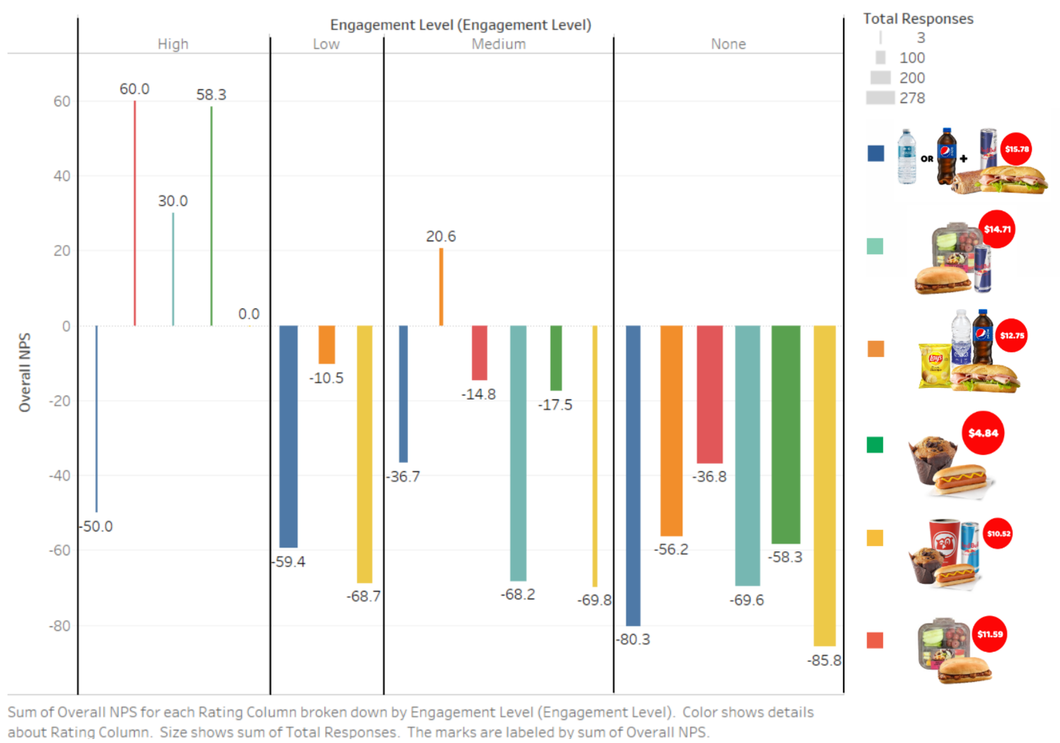

Figure 5: Bar Chart of Combo Offer NPS by Engagement Level

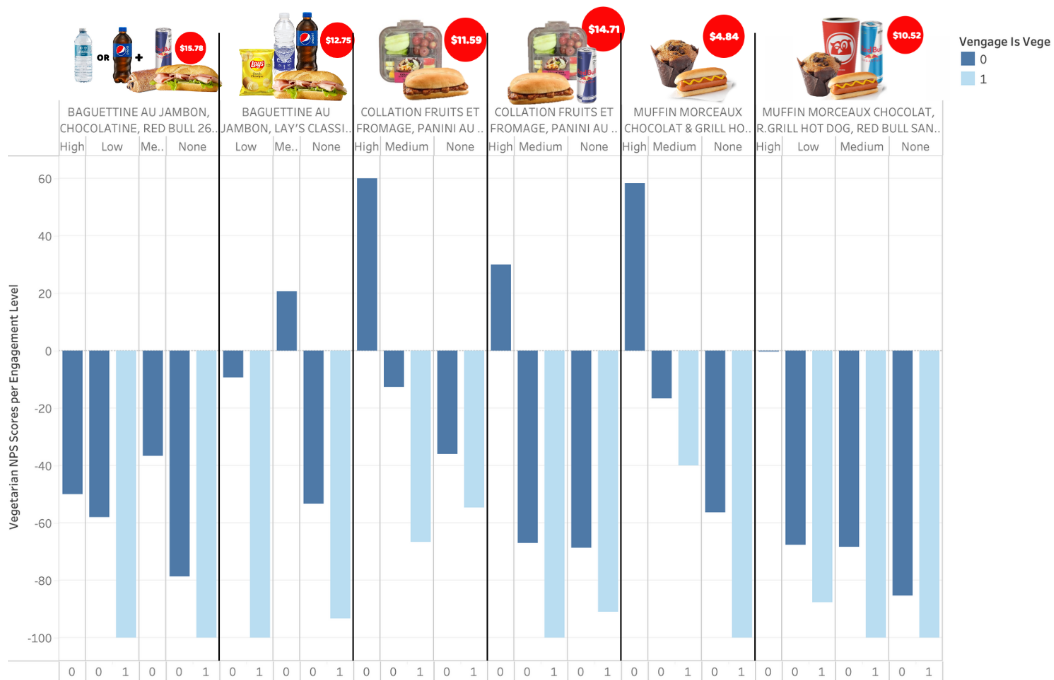

Figure 6: Bar Chart of Combo Offer NPS by Engagement Level and Vegetarian

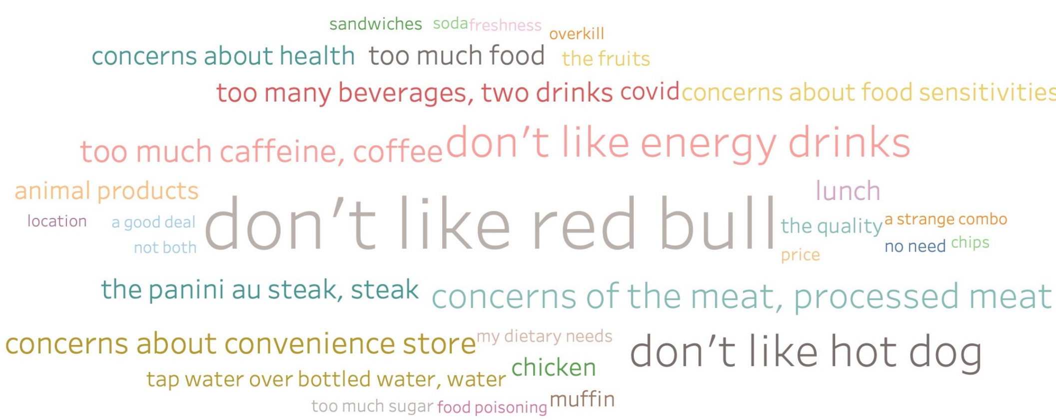

Figure 7: Word Cloud of Cleaned Comments

COLLATION FRUITS ET FROMAGE + PANINI AU STEAK or *VEGAN SANDWICH*

COLLATION FRUITS ET FROMAGE + PANINI AU STEAK + RED BULL 260ML or *PEPSI 610ML*

Figure 8: Illustration of Final Combo Offer Recommendation

Figure 9: Illustration of Recommended Bundle Communication

References

[1] Alimentation Couche-Tard Inc. Corporate couche-tard. `https://corporate.couche-tard.com`, 2024. Accessed: April 16, 2025.

[2] Maxime C. Cohen and Georgia Perakis. Promotion optimization in retail. *SSRN Electronic Journal*, 2018. Available at SSRN: `https://ssrn.com/abstract=3194640`.

[3] Oskar Triebe, Hansika Hewamalage, Polina Pilyugina, Nikolay Laptev, Christoph Bergmeir, and Ram Rajagopal. NeuralProphet: Explainable Forecasting at Scale. *arXiv e-prints*, page arXiv:2111.15397, November 2021.