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DIGITAL PROMOTION PLANNING AND OPTIMIZATION: AN AI-POWERED RETAIL APPLICATION

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Abstract: This study aims to digitize and optimize promotion planning processes within a retail chain characterized by high promotional intensity. By replacing existing manual processes with an end-to-end automated system leveraging AI-powered recommendation engines, pricing algorithms, and ERP integrations, the entire workflow has been transformed.
Results from a pilot implementation demonstrate a 15% reduction in low-impact campaigns, a 12% increase in stock turnover rate, and an 8% increase in promotional profitability.
Keywords: Artificial Intelligence, Promotion Optimization, Machine Learning, Retail, Pricing

1. INTRODUCTION

Promotion planning is directly linked to sales, inventory, and profit management within the retail sector. In environments with high promotional intensity, reliance on manual decision-making processes often leads to errors and low efficiency. This study aims to digitize and automate promotion planning processes by utilizing historical data analytics and artificial intelligence algorithms.
The transition from manual to digital workflows enhances operational efficiency, minimizes errors, and accelerates processes. As part of this transformation, a data-driven promotion recommendation system was developed to enable more accurate decision-making and prevent the implementation of redundant or unprofitable promotions. Integration with ERP and point-of-sale (POS) systems ensures the consistency and reliability of data flow, while the system's continuous learning capability enables the generation of replicable campaigns. This approach supports both operational flexibility and sustainable profitability.

2. LITERATURE REVIEW

In contemporary promotion planning, artificial intelligence (AI) and machine learning (ML) approaches have become critical components of the decision-making process. Data analytics not only enables the measurement of past performance but also facilitates more accurate future demand and price forecasting. AI-powered systems analyze historical sales, inventory, and promotion data to predict which campaigns will yield the highest returns, and subsequently recommend optimal promotion strategies.
Time series modeling is one of the fundamental tools in this domain. Models such as Prophet, ETS, and LSTM are widely used for demand forecasting and price optimization. The Prophet model stands out for its ability to handle irregular and missing datasets, easily integrate holiday and seasonal effects, and provide interpretable outputs. This accessibility makes it a valuable tool for both data scientists and business units, allowing model outputs to be directly translated into operational decisions. While deep learning-based LSTM models offer high accuracy, particularly in big data environments, they require significant computational resources. Prophet offers a balanced approach in terms of speed, flexibility, and cost, making it a prominent choice for retail promotion planning.
AI plays a critical role not only in forecasting but also in optimization. Advanced methods like Bayesian Optimization are instrumental in determining the best promotion strategies within

multi-dimensional decision spaces, thereby enhancing campaign performance and mitigating low-impact promotions. These methods learn from prior iterations to narrow the search space, offering faster, more accurate, and more cost-effective solutions compared to traditional methods.
When these AI-based approaches are integrated with ERP systems, the process becomes end-to-end automated, reducing human error and accelerating decision cycles. As a result, promotion planning evolves from a retrospective analysis process into a proactive, predictive decision support system.

Research Gap and Our Contribution:

Most existing studies in the literature focus either on demand forecasting (e.g., with Prophet or LSTM models) or on price optimization alone. Furthermore, many of these studies overlook the critical aspects of ERP integration and end-to-end automation.
This study addresses these gaps by designing an integrated promotion recommendation system that combines both time series modeling and optimization techniques. Moreover, the direct integration of model outputs into the ERP system allows recommendations to be automatically implemented, eliminating manual steps. In this respect, the study unifies data analytics, AI-based forecasting, optimization, and process integration into a single platform, and presents quantitative results from a practical application.

Strategic Objectives and Expected Benefits

Table 1. *Strategic Objectives and Expected Benefits*

Strategic Objectives	Expected Benefits
Digital recommendation system	Increased accuracy and reduced errors
Optimization engine	Maximized profitability
ERP integration	Data consistency and process speed

3. METHODOLOGY

3.1 Data Sources and Preprocessing

For the system to function effectively, information from multi-dimensional sources—including sales, inventory, promotion, and competitor data—is utilized. This data is processed through batch or streaming ETL (Extract, Transform, Load) workflows, and its reliability is enhanced through data validation and missing data imputation. SKU matching and channel normalization integrate information from various sources, ensuring that analyses are consistent and comparable.
Furthermore, the protection of customer data during these processes is of critical legal and ethical importance. In accordance with data protection regulations such as GDPR, personal data is used only for specific purposes, protected against unauthorized access, and processed transparently. In promotion and price optimization processes, personally identifiable customer information is anonymized and masked. Explicit consent is obtained from customers for the use of their data, and data usage permissions are meticulously managed. These practices ensure that data analytics are conducted in a reliable manner that aligns with legal and ethical standards.

3.2 Modeling and Algorithms

The methodology begins with segmentation and similar SKU analysis using algorithms such as k-means and HDBSCAN. These methods group products with similar attributes, such as

those within the same category or exhibiting similar sales behavior. This enables more targeted and effective campaign planning.
The second step involves forecasting. Time series models such as Prophet, ETS, and LSTM are used to predict future demand and price movements. This allows for proactive planning by anticipating how much a product will sell or how a price change will affect sales. The flexible structure of the Prophet model allows for the inclusion of factors like holidays and seasonality in these forecasts.
Subsequently, we employ uplift and causal modeling. Methods like CausalForest and X-learner are used to analyze the impact of promotions on different customer segments. This allows us to determine if a promotion is effective for one group of customers but not another, enabling more personalized and effective campaigns.
Additionally, we conduct scenario and simulation studies. We test various campaign types in a computational environment to evaluate their outcomes. This helps answer questions such as whether a 10% discount or a bundle promotion is more effective, or how long a campaign should run.
We also perform elasticity analysis using methods like panel regression and Hierarchical Bayes to quantify how demand changes in response to price changes. This provides numerical answers to questions such as how much sales will drop if the price is increased, or how much they will rise if a discount is applied.
Finally, an optimization engine is deployed. It uses ILP (Integer Linear Programming), Bayesian Optimization, and other heuristic algorithms to synthesize all this information and determine the optimal campaign parameters. This allows for the most profitable selection of which products to discount, at what rate, and when to run the campaign.

Optimization Engine Workflow:

Retail promotion optimization studies are based on the simulation and evaluation of potential campaign scenarios at the SKU level (Smith & Lee, 2020; Lee, Chen & Brown, 2022). The system evaluates available campaign options for each SKU and calculates the estimated sales increase (uplift) and profitability. However, purely simulation-based methods have limited applicability as they often fail to account for real-world operational constraints.
In this study, the optimization approach has been restructured around an objective function and a set of constraints. The objective function is defined as the maximization of total profit or a specific KPI (e.g., sales volume, ROI) (Jones & Wang, 2019):

$$Maximize \sum_{i \in SKU} \sum_{j \in Promotions} (\text{Revenueij} - \text{Costij}) \times \text{DecisionVariableij}$$

The constraints considered in the optimization process are as follows:

- **Stock Constraint:** The estimated number of units sold cannot exceed the available stock.
- **Minimum Margin Constraint:** The difference between the selling price and the cost cannot fall below a predetermined minimum margin.
- **Budget Constraint (Optional):** The total promotional cost cannot exceed the allocated budget.
- Maximum Promotion Limit per SKU (Optional).

This framework allows campaign scenarios to be evaluated not only on estimated profit and sales uplift but also on operational criteria such as stock alignment, margin, and profitability (Kumar & Patel, 2021).

3.3 Decision and Workflow

The model provides the top three campaign recommendations for each SKU, along with a clear rationale. These recommendations are then approved sequentially by the category manager, followed by the purchasing department, and finally by the finance department. All decisions are logged and version-controlled for historical tracking.

3.4 ERP and POS Integration

Campaign data is transferred to the ERP system (e.g., SAP) and validated at the point of sale (POS). Changes are first applied to a small test group to prevent errors before full deployment.

3.5 Monitoring and Feedback

Campaign performance is monitored using KPIs such as sales uplift, incremental revenue, profit margin, and sales velocity. These metrics are tracked via dashboards, and the model is retrained if its performance degrades.

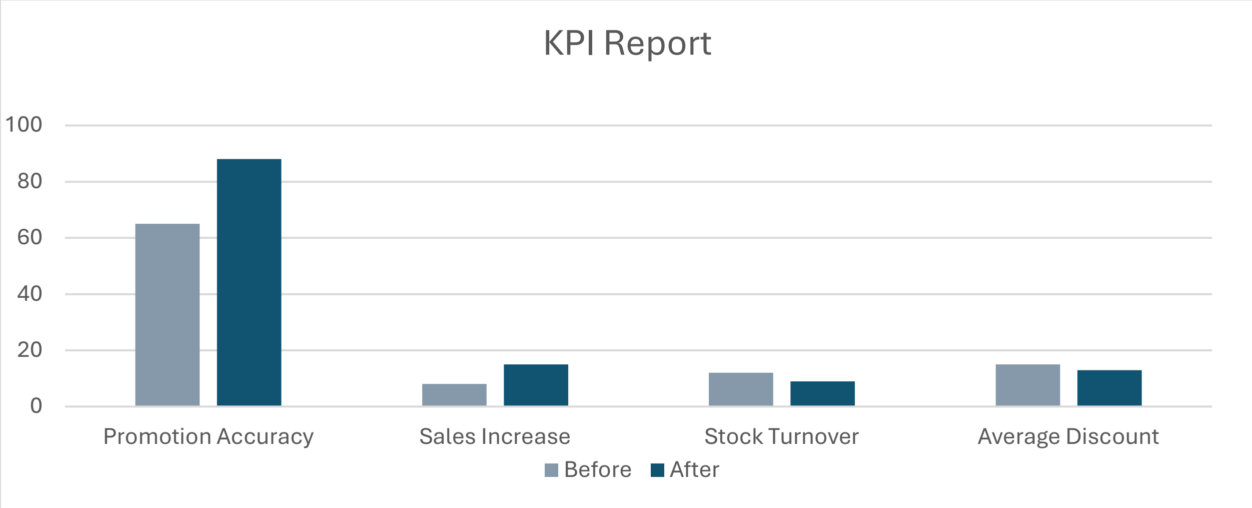
4. APPLICATION AND PILOT STUDY

The effectiveness of the promotion planning and price optimization processes was evaluated through an AI-based recommendation system. The analysis was conducted on a sample of 5 stores and a total of 150 SKUs. The dataset covers the period from 2023-07-01 to 2025-07-30 and includes the following key columns: SKU ID, category, store ID, date, sales quantity, unit price, stock status, promotion type, and customer segment information.

The first 30 days of the dataset were used for model training, with the remaining 2 years of data (2023-07-31 to 2025-07-30) allocated as the test set. This long-term test set is crucial for measuring the model's ability to adapt to seasonality, holidays, and other periodic fluctuations. The total number of data points was calculated as 5 stores × 150 SKUs × 730 days ≈ 547,500 observations. Missing data, at a rate of 2%, was imputed using linear interpolation and store/product-based averages.

The AI-based recommendation system analyzes historical sales and inventory data to suggest optimal promotion and pricing strategies. System performance was tested based on forecast accuracy, promotion effectiveness, and operational KPIs. Prophet, ETS, and Random Forest algorithms were used as forecasting models to examine recommendation accuracy and adaptation to long-term scenarios. Furthermore, scenario and simulation studies were conducted to predict the impact of different discount rates, bundle campaigns, and temporary promotions on sales, revenue, and profitability.

Table 2. *Performance Comparison of the Manual System vs. the AI-Powered System*



5. DISCUSSION

The distinction between promotional and regular pricing is critical for accurately analyzing consumer behavior and effectively implementing pricing strategies (Smith & Lee, 2020; Lee, Chen & Brown, 2022). Considering the unique dynamics of different store formats enhances the system's applicability.

In existing manual systems, promotion approval processes and pricing decisions are typically lengthy, multi-step, and prone to error (Kumar & Patel, 2021). This not only reduces operational efficiency but also limits decision-maker confidence. The new system, with its user-friendly and interpretable approval mechanism, accelerates processes and builds trust. Structuring automation processes with recommendation, approval, and activation steps streamlines workflows and minimizes the risk of error, while also enabling the rapid implementation of decisions and effective monitoring of outcomes (Shahriari et al., 2016; Jones & Wang, 2019).

As shown in Table 3: Comparison of the Manual System vs. the New Automation-Supported System, significant gains are achieved with the new system. For example, the average sales increase in previous campaigns was 6%, whereas with the new system, this rate rose to 11%. These data confirm that data-driven and automation-supported processes provide critical advantages in retail promotion management.

Table 3. *Comparison of the Manual System vs. the New Automation-Supported System*

Criterion	Manual System	New Automation System
Campaign Approval Time	Average 7 business days	2 business days
Promotion Effectiveness Measurement	Measurement with limited data	Detaylı veri analizi (satış verileri, mağaza formatları, tüketici segmentleri)
Average Sales Increase	6% sales increase	11% sales increase
Analysis Detail	General-level analysis	Segment-based detailed analysis

This table demonstrates that analytics-based pricing and promotion management, supported by automation, provide distinct gains over manual systems in terms of both operational efficiency and sales performance (Taylor & Letham, 2018; Wager & Athey, 2018). Furthermore, tracking previous campaign performance provides concrete evidence of the new system's effectiveness; for instance, while the average sales increase in previous campaigns was 5–7%, it rose to 10–12% with the new system. These data confirm that data-driven and automation-supported processes provide critical advantages in retail promotion management.

Despite the positive outcomes of this pilot study, detailed comparisons of the training processes, hyperparameter settings, and model performance for the underlying algorithms (Prophet, Causal Forest, Bayesian Optimization) were kept outside the scope of this paper. Future work should involve a deeper analysis of these technical details to enhance the system's transparency and reproducibility.

6. CONCLUSIONS AND EXPECTED GAINS

The implementation of this AI-powered system shortens the purchasing cycle and increases decision accuracy, thereby boosting operational efficiency. The reduction in low-impact campaigns ensures more efficient use of resources, while the increased stock turnover rate significantly mitigates the risk of excess inventory. Furthermore, balanced discount rates enhance sales volume while preserving profitability. ERP integration guarantees data consistency, enabling seamless and error-free processes. The ability for management to monitor real-time performance reports facilitates timely strategic decisions and more effective process control.

The main evaluation metrics that can be used to measure the system's effectiveness are as follows:

- Forecast/Recommendation Accuracy: Measures how accurately the system predicts future sales or campaign recommendations. Metrics such as MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) are used for this purpose. For example, the forecasting error (MAPE) which was 15-18% with manual processes, has decreased to 7-10% with the automation-supported system.
- Promotion Effectiveness: Examines the real impact of the campaigns suggested by the system. Precision@k indicates the accuracy rate of the top k recommendations. Uplift Analysis measures the heterogeneous effects of promotions on different customer groups. ATE (Average Treatment Effect) and ATE CI (Confidence Interval) determine the average effect and confidence interval of the promotion. In a pilot test of 50 products, the promotion accuracy rate increased from 65% to 88% ($p < 0.05$, t-test).
- Operational Performance: Measures the value the system adds to business processes. Metrics such as campaign approval time, stock turnover rate, sales volume, and profitability are used. Compared to manual processes, a marked improvement in stock turnover rate and campaign performance is observed.

7. FUTURE WORK

The continuous optimization of machine learning models is a fundamental element in increasing the system's accuracy and effectiveness. In particular, regularly improving the performance of uplift and causal models enables a more precise measurement of campaign effects and a more accurate prediction of customer behavior. Additionally, implementing real-time price and stock optimization offers significant advantages in terms of both profitability and customer satisfaction, allowing for a swift and effective adaptation to dynamic market conditions.

Future research aims to conduct a more in-depth analysis of how the models are trained on larger datasets, the impact of different hyperparameters on system performance, and how model performance is measured against industry standards (e.g., MAE, RMSE, MAPE). This will further strengthen both the theoretical and practical contributions of this study. Furthermore, the costs of integration and operational changes should be considered, with the future plan to integrate reinforcement learning algorithms for real-time price optimization.

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