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# A BUSINESS INTELLIGENCE SIMULATOR FOR SALES OPTIMIZATION USING A MACHINE LEARNING DDS FRAMEWORK

*Nabil El Kadhi* [(a)1] *Maruf Fatima Sadriwala* [(b)] *Kaneez Fatima Sadriwala* [(c)] *Rifat O. Shannak* [(d)] *Marwan Alshar'e* [(e)]

[(a)]*Associate Professor, VPAA and Computer Science Department, Applied Science University, Manama, Bahrain; E-mail: Nabil.elkadhi@asu.edu.bh*
[(b)]*Assistant Professor, Pacific University, Faculty of Commerce and Management, India; E-mail: marufsadri@gmail.com*
[(c)]*Associate Professor, College of Economics, Management and Information Systems, University of Nizwa, Sultanate of Oman; E-mail: kaneez@unizwa.edu.om*
[(d)]*Professor, Business School, Jordan University, Amman, Jordan, E-mail: rshannak@ju.edu.jo*
[(e)]*Associate Professor, Faculty of Computing and IT, Sohar University, Sohar, Oman; E-mail: mshare@su.edu.om*

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ABSTRACT

*Existing business intelligence (BI) systems are predominantly descriptive and offer limited support for actionable decision-making in sales optimization, leading to a disconnect between data analytics and operational management. This study examines the development of a unified BI simulator that integrates machine learning, Pareto-based diagnostics, and what-if simulation to support data-driven sales optimization. The research employs an empirical pizza sales dataset from Kaggle, consisting of transactional, temporal, and operational variables. It applies multiple machine learning algorithms for comparative evaluation, along with Pareto analysis to identify key product contributors and a simulation engine to assess the sensitivity of low-performing products to operational changes. The results reveal that the Random Forest model outperforms other models, achieving 97.5% accuracy, an F1-score of 0.941, and an AUC of 0.996. Pareto analysis shows that approximately 30% of product categories account for nearly 80% of total sales, while a small proportion of products consistently exhibit low demand. Additionally, simulation analysis indicates that variations in operational factors, such as delivery efficiency, delivery distance, and product complexity, result in sales variability of up to 12.8%. The findings of this study suggest that the integration of predictive, diagnostic, and simulation-based analytics within a unified BI framework enables precise identification of key sales drivers and quantitatively measures the responsiveness of low-performing products to operational changes, thereby offering a comprehensive and data-driven evaluation of sales performance.*



## INTRODUCTION

In highly competitive markets for retail trade and service delivery, organisations are increasingly implementing advanced business intelligence (BI) tools to analyse sales performance and customer behaviour (Hoang & Bui, 2023; Paulino, 2022). Despite the mass adoption of dashboards and descriptive analytics, most BI solutions to date have been largely reactive, focusing on historical reporting and providing little to no support for prescriptive, actionable decision support to alleviate poor performers within product lines (Al-Okaily et al., 2023). Managers often identify what sells, but they lack systematic approaches to explain the factors behind poor performance and to develop specific interventions to improve sales (Khatuwal & Puri, 2022; Sorour & Atkins, 2024). The most recent advances in machine learning (ML) technologies have enhanced predictive analytics in the retail setting in distinctive ways (Koner et al., 2024; Punia & Shankar, 2022). However, the smooth integration of these capabilities with current BI systems is distinctly limited (Paramesha et al., 2024; Rane et al., 2024). Existing academic research is mostly preoccupied with sales prediction or consumer market segmentation, and little attention is paid to explainability, scenario-based arguments, or practical operational suggestions (Islam & Hasan, 2023).

[1]Corresponding author: *ORCID ID: 0000-0002-8139-320X*

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Therefore, a critical misalignment emerges between machine-learning-fueled predictions and their practical application in managerial decision-making, especially regarding low-selling products whose impact requires accurate and cost-efficient interventions (Hou et al., 2023; Wang et al., 2023)

The current study bridges this gap by proposing a smart business intelligence simulator that leverages the benefits of explainable machine learning, Pareto-based sales diagnostics, and 'what-if' simulation in a coherent decision-support framework. The system is designed as an open, scalable BI toolkit that can streamline sales of any product (Gorgilli et al., 2025). The framework was instantiated and applied to a realistic dataset of pizza sales, available on Kaggle, using transactional, temporal, and operational variables.

This contribution is carried out in three dimensions. To begin with, it offers an explainable ML-based BI framework that extends beyond descriptive analytics (Salimparsa et al., 2025), enabling the identification of the predominant factors underlying product selection. Second, it presents a what-if simulation unit that quantitatively evaluates the potential sales boost from tactical operations and marketing actions (Opara et al., 2025). Third, it ends with a managerial dashboard that combines sales ranking, Pareto analysis, identification of low sellers, and ML-generated recommendations on the user interface, creating a single, understandable view-all dashboard (Zamil et al., 2024). These improvements aim to develop a smart BI system that is redesigned as an active decision support tool to ensure optimal sales productivity.

To address the optimal sales productivity concern, this work uses a machine learning and design science approach to develop a business intelligence simulator that combines predictive analytics, Pareto-based diagnostics, and scenario construction.

The goal of this paper is to design and test a business intelligence simulator for sales optimization that incorporates machine learning, diagnostic analysis, and simulation.

This work is structured as follows. Section II provides a literature review of business intelligence, machine learning and sales optimization. Section III provides the materials and methods and outlines the proposed system and approach, including the data and techniques used. Section IV provides results, discusses the experimental findings and evaluation and demonstrates the developed simulator for sales optimization. Finally, Section V concludes the study.

## LITERATURE REVIEW

The dynamic business environment, evolving consumer demands, and the ubiquity of information have increased the complexity of doing business (Gupta et al., 2022; Liu et al., 2010). The requirement for decision support systems evolved from systematizing decision-making processes, backing up decisions with data proofs, enhancing data observation, overcoming the limitations of manual processes, and identifying and addressing process gaps (Sutton et al., 2020). The existing literature clearly identifies certain drawbacks of the DSS. In view of past studies, two main gaps emerge in the existing literature. First, there is limited research that analyses how BI and DSS (decision support systems) actually affect retail organization performance and which factors drive their success (Islam & Ikbal, 2022). The effectiveness and appropriateness of these tools have not been examined in depth. Second, implementation challenges specific to the retail sector remain under-explored. The literature lacks detailed insight into the barriers retailers face when adopting BI and DSS, such as data management issues, funding constraints, and skill shortages (Alasiri & Salameh, 2020; Jewel et al., 2024).

In sales, accurate forecasting plays a critical role across several areas, including inventory management, resource allocation, and strategic planning, thereby reducing waste and increasing efficiency. Before the current BI (business intelligence) systems, companies traditionally relied on LR (Linear Regression), failing to incorporate multiple factors in the retail environment, such as product families, seasonality, and external factors (Gupta et al., 2022). Another use is where companies make products to order. Precise prediction models help them make inventory decisions and avoid delays and added costs. Traditional methods relied solely on historical data, which often missed key details. Machine learning eases the compilation of big data and the detection of hidden patterns, which becomes vital in industries such as retail, food, and fashion (Syberg et al., 2023; Zohdi et al., 2022).

AI's potential has had a great impact on CRM. Its capabilities are undeniable for processing large datasets, sales prediction, and customer profiling using tools such as Salesforce, HubSpot, or Zoho (Gupta et al., 2022). However, there are still gaps left unaddressed by AI, the most prominent being the Black-box problem and the challenges of model explainability and transparency. A few other notable concerns highlighted by studies include limited handling of high seasonality and multiple product families, and data security (Prasanth et al., 2023; Shannaq & Alabri, 2025; Vankayalapati, 2020). Therefore, there remains a need for a more robust, integrated system that enables users to make more informed decisions and can be modified to include contextual factors.

The Pareto sales network asset has been used as the 80/20 concept in sales management, prioritizing high-impact members such as key distributors, large customers and channel partners that have a disproportionately large contribution to the company's sales performance (Ab Talib et al., 2015; Ferdinand & Killa, 2018; Jum'a & Basheer, 2023).

What if simulations, also called WIA (What If Analysis), work in a very intuitive way in the field of marketing, operations and sales, where they let managers change certain variables such as number of campaigns, use of different platforms for shooting the advertisements or email blasts to predict the resulting acquisition rates and choose a scenario that results with the highest acquisitions with the lowest resultant cost. WIA can also be used in the supply chain to address uncertainty, predict demand spikes, and assess the impact of centralised versus decentralised planning structures. Scenario trees can help integrate demand elasticity models to jointly optimize assortment, inventory, and promotions, thereby improving profit versus heuristic or forecast-only approaches (Ben Rabia & Bellabdaoui, 2022; Gathani, Liu et al., 2025; Salarpour & Zeinolabedinzadeh, 2025)

Using WIA tools without ML relies solely on manually crafted formulas and static decision tables, making them lack scalability. When new variables are introduced, each factor would require additional rules, leading to a combinatorial explosion and increased maintenance overhead. It would also struggle with uncertainty and inaccurate forecasts. Therefore, its recommendations would become stale and require expensive manual updates (Gathani, Li et al., 2025; Zhang et al., 2025).

This study seeks to overcome the shortcomings of conventional business intelligence (BI) systems, which are mainly descriptive and lack interactive assistance for decision-making, and to present an intelligent business intelligence (BI) simulator for sales optimization. This study aims to develop a holistic approach that integrates explainable machine learning, Pareto-based sales diagnostics, and what-if analysis into a decision-support framework. The system is envisioned as an open, flexible BI toolkit for sales optimization across a range of products. The study has three primary goals. First, it aims to enhance traditional BI methods by building on explainable machine learning methods that allow the discovery of factors that impact product demand and sales. Second, it proposes a simulation module to measure the effects of operational and marketing strategies on sales. Third, it seeks to integrate these various analytical features into a single manager dashboard, offering a holistic, explainable picture of sales performance, including product ranking, Pareto analysis, and data-driven recommendations.

Through these goals, the research helps transform BI systems from basic reporting platforms into interactive, smart decision-making systems that support sales optimization and improve managerial performance.

## MATERIALS AND METHODS

Although there is a long tradition of research on BI systems and machine learning in sales analytics, current methods are mostly descriptive and predictive, offering limited support for explainable, scenario-based decision-making. Specifically, few studies examine how ML insights can be translated into practical recommendations for underperforming products. This work addresses this gap by introducing an intelligent BI simulator that combines explainable AI, Pareto diagnostics, and what-if simulation to provide effective, understandable sales optimization assistance.

We present a complex business-intelligence approach in this study that takes standard descriptive analytics to the next level by combining interpretable machine-learning algorithms, Pareto-based diagnostics, and what-if analysis to deliver actionable decision-support solutions. Unlike existing BI solutions, the suggested solution not only identifies sub-optimally operating items but also explains the causal factors behind their poor performance and provides quantitative simulations of possible improvement strategies. The framework is designed as a generic, extensible simulator, making it potentially applicable to a wide variety of product areas. The framework includes the following components/steps:

- Data Acquisition: The goal of this step is to collect transactional, temporal and operational sales data for pizza sales from the Kaggle system: (https://www.kaggle.com/datasets/akshaygaikwad448/pizza-delivery-data-with-enhanced-features/data).
- Data Preprocessing: This step involves cleaning data, encoding categorical variables, and normalizing numerical attributes.
- Sales Diagnoses: In this step, products will be ranked by sales, and a Pareto (80/20) analysis will be applied to identify the key and low-selling items.
- ML Model Selection: This is a major step to train and evaluate multiple classifiers, which includes selecting RandomForest based on performance metrics
- Explainable analysis: Based on the previous results, feature importance will be computed to identify the dominant factors influencing product selection.
- Simulation: This step consists of a set of simulations of operational and promotional actions and changes to estimate potential sales uplift and evaluate their impacts.

## RESULTS

This section outlines the main empirical findings from the proposed smart Business Intelligence simulator. The discussion focuses on model performance, diagnostics of the sales structure, and the effectiveness of machine-learning-based what-if recommendations. To highlight the actionable implications for managerial decision-making, we have limited ourselves to the most informative tables and figures.

### Model Performance Evaluation

The comparative analysis of the classification models revealed that the Random Forest classifier significantly outperforms the other alternatives, with an area under the curve of 0.996, an F1-score of 0.941, and an accuracy of 97.5 per cent (Table 1: Model Comparison). These scores support the strength of RandomForest in the face of a heterogeneous combination of numerical and categorical sales data in this setting, making it a worthy choice as the central analytical engine of the simulator.

Table 1. Model Comparison

| Model | AUC_mean | AUC_std | F1_mean | F1_std | Accuracy_mean | Accuracy_std | CombinedScore(0.6*AUC+0.4*F1) |
|---|---|---|---|---|---|---|---|
| RandomForest | 0.996461 | 0.001592 | 0.940855 | 0.010696 | 0.9751 | 0.00445 | 0.974219 |
| GradientBoosting | 0.989338 | 0.0076 | 0.943812 | 0.012112 | 0.97609 | 0.004911 | 0.971128 |
| LogisticRegression | 0.964205 | 0.017397 | 0.86262 | 0.011399 | 0.939239 | 0.003794 | 0.923571 |
| BernoulliNB | 0.882425 | 0.014149 | 0.360809 | 0.091778 | 0.831667 | 0.012437 | 0.673778 |

**Sales Structure and Pareto Analysis**

The highly skewed distribution of sales is revealed through Sales ranking and Pareto analysis (Figure 1: Pareto Analysis of Pizza Types). Only a few types of pizza account for nearly 80 per cent of all sales, and the bottom 20 per cent of products continue to underperform (Table 2: Low-Selling Pizza Types). This fact supports the need to implement specific interventions and not general promotion efforts.

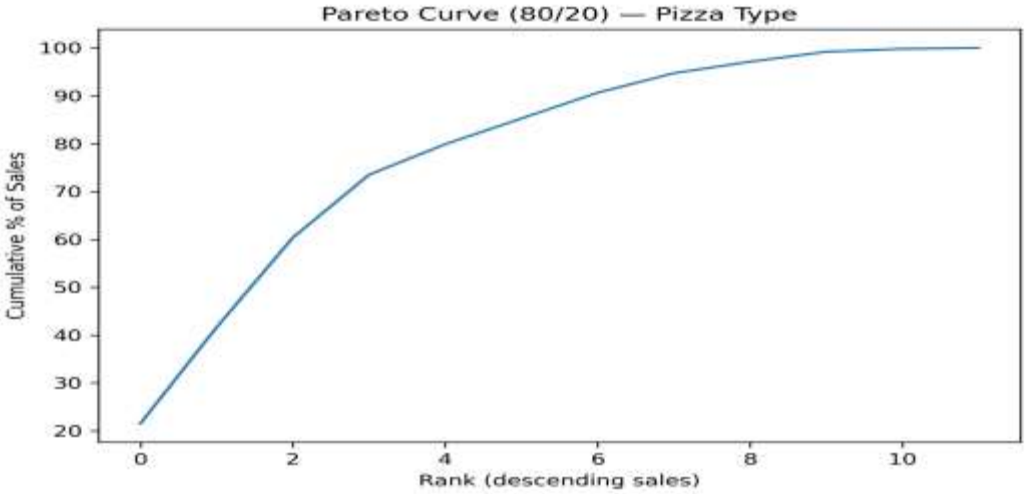



Figure 1. Pareto Analysis of Pizza Types

Table 2. Low-Selling Pizza Types

| Pizza Type | Sales |
|---|---|
| Thin Crust | 2 |
| Deep Dish | 6 |
| Stuffed Crust | 21 |

***The Major Influencing Factors in the choice of products***

The global feature-effect ranking (Table 3: Global Field Effect Ranking) identifies the following factors as the best determinants of product choice: delivery time, delivery range, peak-hour ordering, and pizza complexity. These results provide clear evidence that customer purchasing behaviours are directly related to operational parameters.

Table 3. Sample Global Field Effect Ranking

| BaseField | TotalImportanceMean | TotalImportanceStd | EncodedFeaturesCount |
|---|---|---|---|
| Topping Density | 0.083 | 0.011 | 1 |
| Pizza Complexity | 0.053 | 0.008 | 1 |
| Order Month | 0.038 | 0.021 | 12 |
| Pizza Size | 0.033 | 0.016 | 4 |
| Distance (km) | 0.031 | 0.002 | 1 |
| Estimated Duration (min) | 0.031 | 0.002 | 1 |
| Delivery Time | 0.030 | 0.007 | 980 |
| Order Time | 0.030 | 0.006 | 968 |
| Order_Hour | 0.029 | 0.008 | 1 |
| Order Hour | 0.029 | 0.008 | 1 |
| Location | 0.027 | 0.028 | 84 |

**What-If Simulation/ Sales Uplift**

Table 4. What-If Sales Uplift. The results of the what-if simulation show that operational and promotional changes have a significant effect on low-selling products. Sales uplifts from simulated intervention projects are close to 12.83 when delivery time and distance restrictions are lifted or when peak-hour services are uniquely designed.

Table 4. What-If Sales Uplift

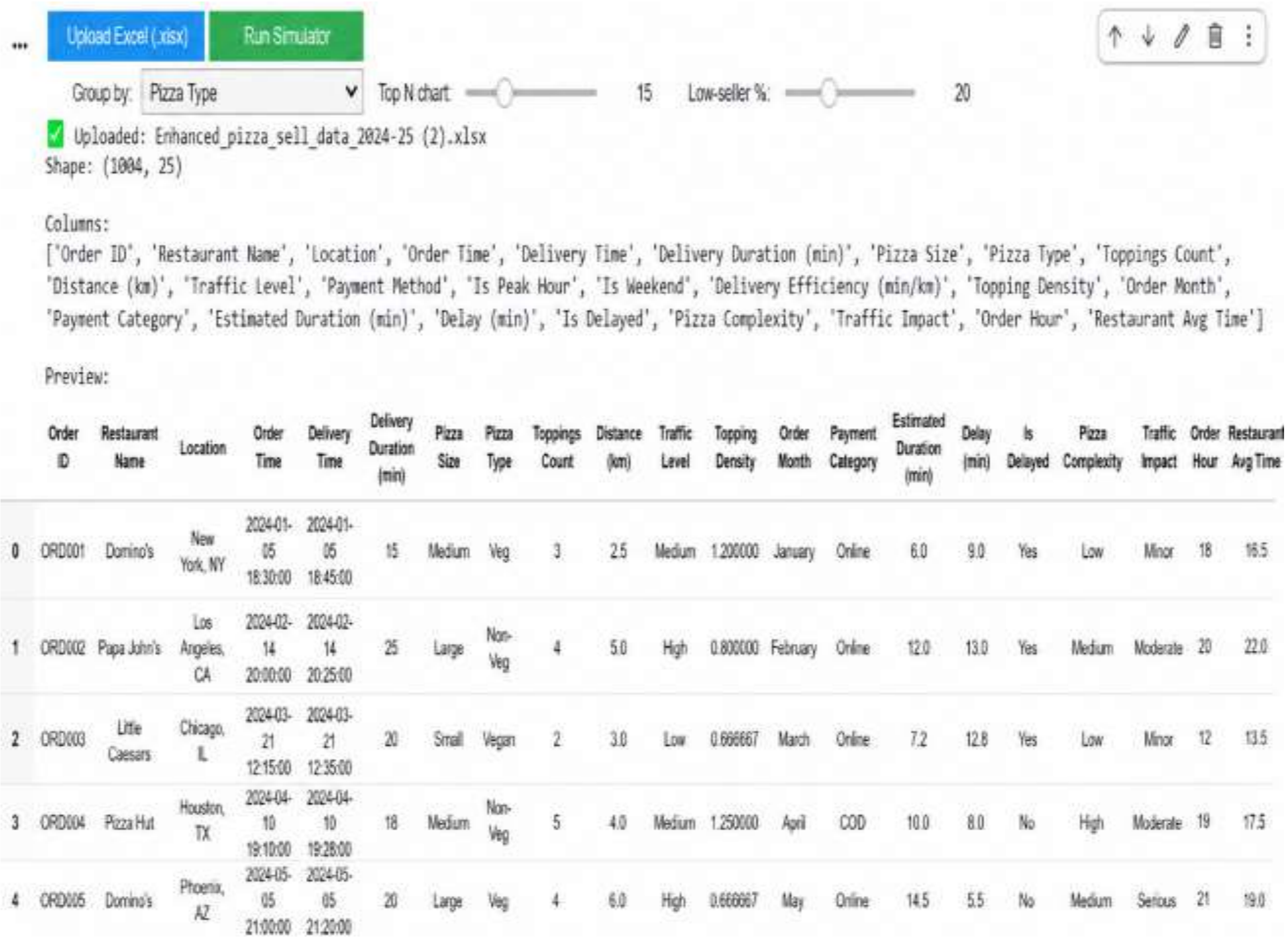
| Pizza | Scenario | Baseline_Prob | New_Prob | Expected_Uplift_% |
|---|---|---|---|---|
| Thin Crust | PeakHour_Promotion | 0.884 | 0.884 | 0 |
| Deep Dish | PeakHour_Promotion | 0.770333 | 0.770333 | 0 |
| Thin Crust | Reduce_DeliveryTime_20pct | 0.884 | 0.882 | -0.226244344 |
| Thin Crust | Simplify_Toppings | 0.884 | 0.876 | -0.904977376 |
| Deep Dish | Simplify_Toppings | 0.770333 | 0.732333 | -4.932929468 |
| Thin Crust | Reduce_Distance_15pct | 0.884 | 0.82 | -7.239819005 |
| Deep Dish | Reduce_DeliveryTime_20pct | 0.770333 | 0.705333 | -8.437905669 |
| Deep Dish | Reduce_Distance_15pct | 0.770333 | 0.672 | -12.76503678 |

**Unified Smart BI Dashboard**

The simulator dashboard (Figure 2-7: Unified Sales and ML Decision Dashboard) unites sales ranking and Pareto diagnostics, machine-learned identification of low sellers, and machine-learned uplift scenarios in a single visual control. This dashboard converts analysis results into practical suggestions, helping managers quickly pinpoint underperforming items and prioritize data-driven strategies to improve them. Theral language processing was built upon the work.


Figure 2. Pizza Sales Simulator 1


Figure 3. Pizza Sales Simulator 2




| | Order ID | Restaurant Name | Location | Order Time | Delivery Time | Delivery Duration (min) | Pizza Size | Pizza Type | Toppings Count | Distance (km) | Traffic Level | Topping Density | Order Month | Payment Category | Estimated Duration (min) | Delay (min) | Is Delayed | Pizza Complexity | Traffic Impact | Order Hour | Restaurant Avg Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | ORD001 | Domino's | New York, NY | 2024-01-05 18:30:00 | 2024-01-05 18:45:00 | 15 | Medium | Veg | 3 | 2.5 | Medium | 1.200000 | January | Online | 6.0 | 9.0 | Yes | Low | Minor | 18 | 16.5 |
| 1 | ORD002 | Papa John's | Los Angeles, CA | 2024-02-14 20:00:00 | 2024-02-14 20:25:00 | 25 | Large | Non-Veg | 4 | 5.0 | High | 0.800000 | February | Online | 12.0 | 13.0 | Yes | Medium | Moderate | 20 | 22.0 |
| 2 | ORD003 | Little Caesars | Chicago, IL | 2024-03-21 12:15:00 | 2024-03-21 12:35:00 | 20 | Small | Vegan | 2 | 3.0 | Low | 0.666667 | March | Online | 7.2 | 12.8 | Yes | Low | Minor | 12 | 13.5 |
| 3 | ORD004 | Pizza Hut | Houston, TX | 2024-04-10 19:10:00 | 2024-04-10 19:28:00 | 18 | Medium | Non-Veg | 5 | 4.0 | Medium | 1.250000 | April | COD | 10.0 | 8.0 | No | High | Moderate | 19 | 17.5 |
| 4 | ORD005 | Domino's | Phoenix, AZ | 2024-05-05 21:00:00 | 2024-05-05 21:20:00 | 20 | Large | Veg | 4 | 6.0 | High | 0.666667 | May | Online | 14.5 | 5.5 | No | Medium | Serious | 21 | 19.0 |

Figure 4. Pizza Sales Simulator3

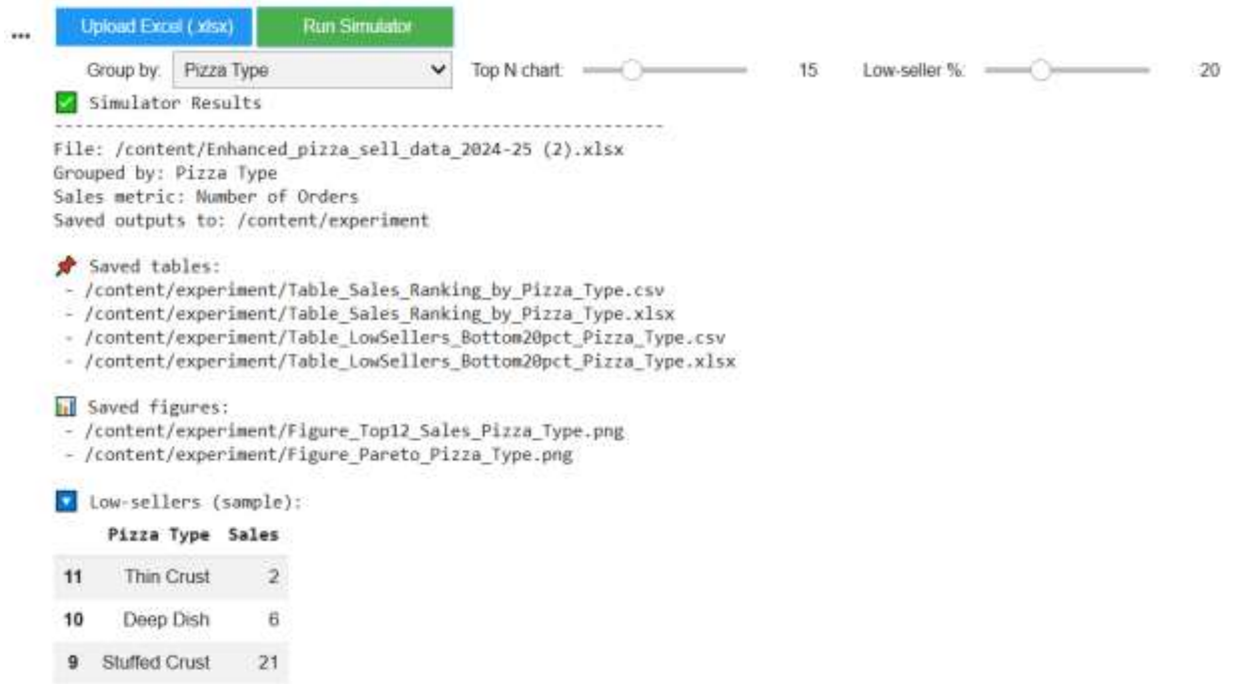



Figure 5. Pizza Sales Simulator 4

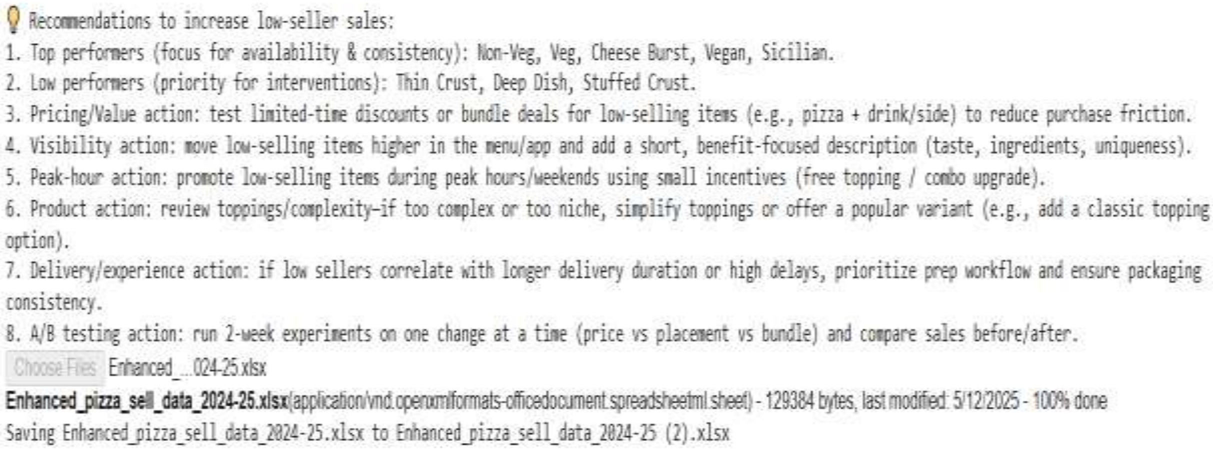



Figure 6. Pizza Sales Simulator (Summary)

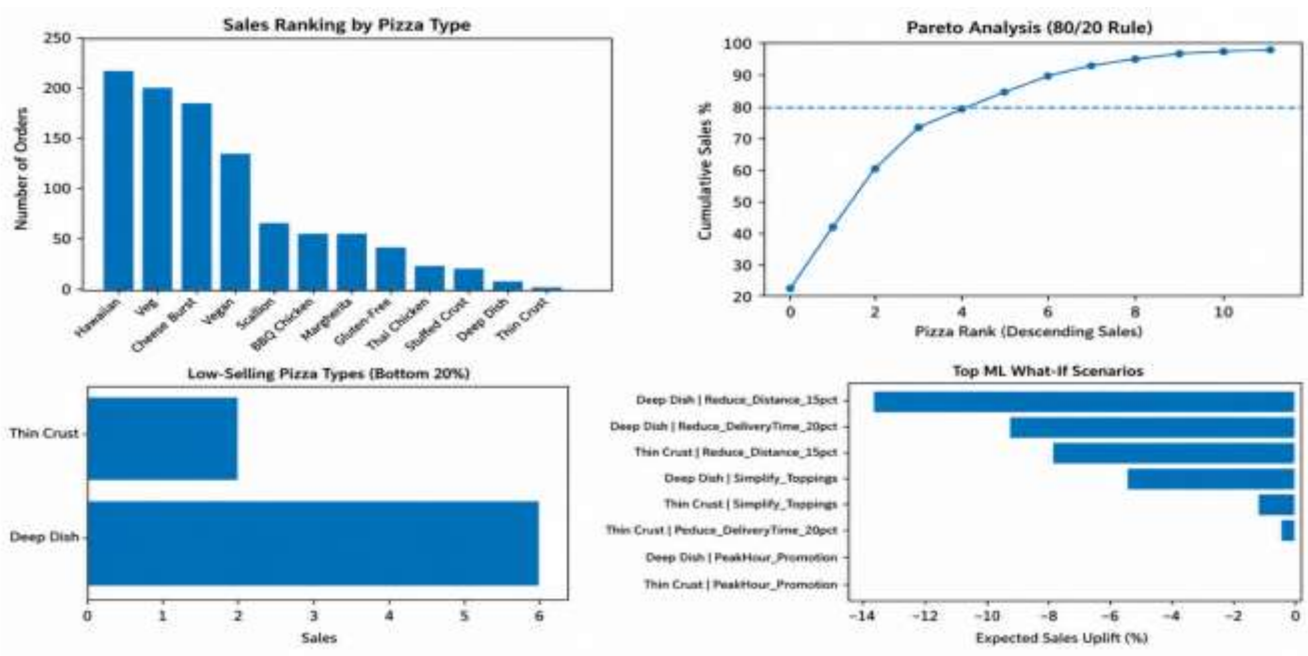



Figure 7. Unified Sales and ML Decision Dashboard

## CONCLUSIONS

This research focused on designing and testing a business intelligence simulator that combines machine learning, diagnostic analytics and simulation to drive data-informed sales strategies. The results show that the developed approach successfully extends conventional BI systems by integrating predictive analytics, diagnosis based on the Pareto principle, and what-if simulation within a single decision-making environment. This study used a pizza sales dataset to demonstrate high predictive accuracy (accuracy = 97.5%, F1-score = 0.941, AUC = 0.996) for the Random Forest model and that 30% of products account for almost 80% of sales, as confirmed by the Pareto analysis. Additionally, the simulation module estimated the sensitivity of low-performing products, with up to 12.8% improvements in sales under various operational conditions. This research offers several novelties. First, it links descriptive analytics and decision support through an integrated BI simulator, leverages explainable machine learning to enhance interpretability, and provides a quantitative simulation tool for assessing managerial interventions. Theoretically, it extends BI research by integrating predictive, diagnostic and prescriptive analytics. From a managerial perspective, it provides a pragmatic approach to help managers determine key factors impacting sales, assess low-performing items, and simulate alternative scenarios. The study is limited to a single dataset in a specific retail setting and uses historical (static) data for analysis rather than real-time data. Potential avenues for future research include using real-time data streams, experimenting with other machine learning methods (e.g., deep learning and reinforcement learning), and applying the framework to other domains and datasets.

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