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# Technical paper for Retail business analysis and Strategic actions platform project powered by Data science

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***Abstract*—This technical paper presents the design and implementation of an end-to-end Retail Business Analysis and Strategic Actions platform that transforms raw transactional data into actionable insights—spanning customer segmentation, CLTV prediction, churn risk scoring, product recommendation, promotion timing, inventory forecasting, festive season promotion planning and clearance optimization.**

**These insights are directly linked to business actions such as retention targeting, incentive design, stock planning, discount strategies, and campaign scheduling, enabling a closed-loop system from data to execution.**

**The system integrates modular data processing (Python / pandas), analytical modeling (RFM + K-Means, heuristic & regression CLTV, Random Forest churn, item similarity & sequence transitions, discount elasticity simulation), temporal behavior mining (hourly triggers), and decision support layers (Power BI dashboards + Streamlit interactive GUIs).**

**The platform demonstrates how a retailer can institutionalize data science workflows to drive continuous improvements in business strategies, customer engagement, and operational efficiency.**

## I INTRODUCTION

Retail organizations accumulate rich behavioral signals—orders, product mixes, timing, and repeat patterns—that, when fused, reveal differential lifetime value, attrition risk, and demand curves. Traditional dashboards often stop at descriptive analytics; this work operationalizes prescriptive and actionable intelligence by attaching every analytic layer to a concrete downstream strategy (offer type, timing, inventory, discount, promotion class).

Key applications implemented are as follows:

*A. Value Segmentation & CLTV* RFM + segment scoring plus a regression-style CLTV estimate for prioritization.

*B. Churn Prediction & Revenue Risk* Random Forest model + expected value weighting (CLTV × churn probability).

*C. Recommendation Engines*

(a) Item similarity (cosine over customer–product matrix) for last-item suggestions;

(b) Sequential transition (Markov / top conditional product) for *Next Product Prediction*.

*D. Inventory & Demand Planning* Forecast top 10 SKUs (Prophet [8] fallback → SMA) to pre-stock one month ahead; safety stock heuristics.

*E. Clearance Optimization* Bottom 10 SKUs discount simulation using elasticity & zero-sales ratio to propose discount tiers / discontinue flags.

*F. Promotion Targeting & Timing* Decision Tree promotion class model (VIP loyalty, upsell, save, cross-sell, nurture, win-back) + hourly trigger classifier (HOT / WARM / COLD hours per value tier).

*G. Action Orchestration* Output CSV & GUI layers for retention cohorts, promotion schedules, inventory reorder plans, clearance recommendations, festive season promotion planner.

## II RELATED WORKS

A DEEP PROBABILISTIC MODEL FOR CUSTOMER LIFETIME VALUE PREDICTION [14].

Xiaojing Wang, Tianqi Liu, Jingang Miao

https://arxiv.org/pdf/1912.07753

We referred many articles and found article [14] as a Related work.

Both, aforesaid related work paper [14] and my project focus on Customer Lifetime Value (CLTV) prediction as a core component of customer analytics. The related work paper [15], uses advanced deep probabilistic models to estimate future customer value, while our project also segments customers based on CLTV (Top, High, Medium, Low) and leverages these insights for decision-making. Both aim to help businesses optimize resource allocation, retention strategies, and targeted campaigns by understanding the lifetime value of customers. Additionally, both projects emphasize actionable insights—our project through Power BI dashboards [15] and interactive GUIs, and the related work paper [14] through predictive CLTV modeling.

Our project extends beyond pure CLTV prediction by incorporating churn risk modeling, promotion planning, product recommendation GUIs, and hourly trigger analysis, offering a more comprehensive end-to-end business intelligence solution. Unlike the related work paper's [15] research-oriented probabilistic approach, our system integrates Prophet-based forecasting [8], inventory planning, and clearance sale strategies with interactive Streamlit dashboards [7] for business teams to act on insights in real time. While the related work paper focuses on probabilistic accuracy, our project provides multi-layered insights (behavioral segmentation, product popularity trends, and time-based campaigns), bridging the gap between analytics and direct business execution.

## III LAYER | TOOLS & LIBRARIES | PURPOSE

A. Ingestion & Processing | Python [1], pandas [2],NumPy [3] | Cleaning, feature engineering, aggregation.
B. Modeling | scikit-learn [4] (KMeans, RandomForest, DecisionTree), Prophet [8] , stats heuristics | Segmentation, churn, CLTV, forecasting, promotion classification.
C. Recommenders | Cosine similarity (vectorized), transition frequency matrix | Last-item similar products & next-product prediction.
D. Serving (Visualization) | Power BI [15] | Executive & operations dashboards.
E. Interactive Apps | Streamlit GUIs [7] | Real-time "what-if" & action generation.
F. Persistence | CSV / XLSX (source), model pickles (joblib) | Reproducibility & deployment handover.
G. Automation Assets | Exported action tables (retention_targets, promotion hourly_triggers, top10_forecast_action_plan, clearance_recommendations) | Operational integration

## IV SYSTEM ARCHITECTURE

*A. Source Layer*
Single retail transactions dataset Online Retail II [11] plus E-commerce Behavior [13] and Telco Churn datasets [12] derived analytical tables (CLTV with predictions, churn risk, product transitions, monthly SKU aggregates).

*B. Feature Layer*
RFM metrics, monetary aggregates, temporal features (hour of day, recency), segment labels (A→D remapped to Top/High/Medium/Low), churn flags, product transition counts, volatility & zero-sales ratios for slow movers.

*C. Modeling Layer*
Modular scripts / notebooks produce model artifacts (cltv_model.pkl, churn_model.pkl, promotion_model.pkl) and forecast & risk tables.

*D. Action Layer*
Business-aligned outputs—promotion classes, retention cohorts, revenue at risk ranking, inventory reorder suggestions, discount strategies, recommended hour triggers.
*E. Delivery Layer*

* Dashboards
Multi-page Power BI [15]: CLTV, Churn & Risk, Revenue at Risk, Behavioral Segments (hour × weekday), Next Product Pathways, Top Products Planning, Clearance Planning.

* GUIs
Streamlit micro-apps [7] for Top Products Forecast, Clearance Discount Planner, Promotion Recommender, Festive season promotion planner, Hourly Promotion Trigger Planner.
Refer enclosed Fig. 1 having System architecture.

## V IMPLEMENTATION

*A. Data Preparation*
* Cleaning: Remove negative quantities & zero / invalid prices; drop missing customer IDs.

* RFM: Snapshot = max invoice date + 1 day. Recency (days since last purchase), Frequency (distinct invoices), Monetary (sum spend).
* Standardization: Scale RFM for clustering (KMeans k=4).
* Segment Label Mapping: A→Top, B→High, C→Medium, D→Low (human-readable).

*B. CLTV Estimation*

* Baseline heuristic:

CLTV = AOV × PurchaseFrequency × 365 × ProfitMargin

Where AOV = Monetary / Frequency, PF = Frequency / RecencyPeriod. Enhanced regression (LinearRegression) trained to map transactional features to observed monetary patterns.

*C. Churn & Revenue Risk*

Churn Label Proxy: Recency > threshold or inactivity. RandomForestClassifier on Frequency, Recency, Monetary, AOV, PF, CLTV.

Revenue Risk = CLTV × Churn_Prob ranks save priority.

*D. Recommendation Engines*

* Item Similarity: Customer–Item matrix → cosine similarity to propose "similar" SKUs.
* Sequence / Next Product: Transition counts conditional on last SKU → highest probability next purchase.

*E. Inventory Forecast & Stock Planning*

* Forecast top 10 SKUs using Prophet or 3-month moving average.
* Safety Stock: SS = Z × σ_d √L, with service level and lead time. Suggested Stock = Forecast + SS.

*F. Clearance Optimization (Low Sellers)*

Features: Avg Monthly Qty, Zero Sales Ratio, Months Since Last Sale, Coefficient of Variation.

Discount assignment tiers (30–60%) adjusted by recency & volatility; uplift projected; "Bundle / Discontinue" classification for margin erosion.

*G. Promotion Class Modeling*

Rule engine with classes: VIP_LOYALTY, HIGH_VALUE_SAVE, etc. DecisionTreeClassifier trained on rule outputs.

*H. Hourly Promotion Triggers*

Per segment, aggregate by hour → HOT (≥80%), WARM (50–80%), COLD (<50%). GUI returns optimal hours.

*I. Integrated Promotion Recommendation*

Streamlit app [7] returns promo class, rationale, next product suggestion, hour band.

*J. Festive Season Purchase Behaviour*

Diwali & Christmas festival-driven purchase trends are identified using temporal filtering on invoice dates and NLP-based keyword extraction from product descriptions. SKU-level sales are aggregated per festive window, enabling pre-emptive promotion planning and targeting. A dedicated GUI module facilitates manual discount configuration and promotion window tagging via rule-based logic.

## VI DATA INSIGHT TO BUSINESS ACTIONS

| Analytic Output | Derived Action | Operational Output |
|---|---|---|
| CLTV Segments | Tiered service & budget allocation | cltv_with_predictions.csv |
| Revenue Risk Ranking | Save high-value at-risk first | cltv_with_churn_risk.csv |
| Churn Drivers | Adjust retention levers | Dashboard visualization |
| Next Product Prediction | Upsell / cross-sell placements | Transition table (Power BI / GUI) |
| Item Similarity | Personalized recommendations | Real-time GUI |
| Hourly Trigger Classes | Campaign scheduling windows | promotion_hourly_triggers.csv |
| Top SKU Forecasts | Pre-stock & seasonal promo timing | top10_forecast_action_plan.csv |
| Low Seller Metrics | Discount / bundle / discontinue | clearance_recommendations.csv |
| Promotion Class Model | Targeted offer type selection | promotion_dataset.csv |
| Seasonal Purchase Behavior | Festival-targeted promotion offer planning | festival_top_products.csv + Streamlit GUI |

## VII IMPELEMENATION HIGHLIGHTS

Modular Scripts: Each model (CLTV, churn prediction, product forecast, promotion triggers) outputs both .pkl artifacts and enriched CSVs ready for Power BI [16] integration.
Interactive GUIs: Streamlit [7]-based planners (Top Products Forecast, Clearance Planner, Promotion Trigger) bridge analytics with actionable steps.
Fallback & Reliability: When Prophet [8] forecasting fails, moving averages ensure no pipeline breakage.
Human Interpretability: Rule-based HOT-hour triggers and tier-based discount logic improve stakeholder understanding and trust.
Separation of Concerns: Jupyter notebooks for experimentation → Python [1]scripts for automation → Power BI dashboards [16] and GUIs for visualization.
Performance: Vectorized pandas [2] operations and modular design deliver efficiency and scalability.

## VIII RESULTS & CONCLUSION

Successfully implemented a complete retail customer intelligence and analytics platform that combines CLTV segmentation, churn prediction, product recommendations, and promotion triggers into a unified framework. The Power BI dashboards [15] effectively visualize customer behaviours, product sales trends, and revenue risks, while the Streamlit GUIs [7] provide interactive forecasting and promotion planning tools (e.g., top product forecasting, clearance sale planning, festive season promotion planning and hourly trigger models). Key business insights, such as top & less selling products, customers at risk of churn, and optimal promotion timings, are transformed into actionable strategies like targeted campaigns, inventory planning, discount-based sale or clearance sales. The system not only improves decision-making efficiency but also aligns data analytics directly with operational actions.

## IX FUTURE ENHANCEMENTS

- Integrate real-time data pipelines.
- Adopt advanced AI models for improved predictions.
- Automate targeted campaign execution.
- Deploy the system on scalable cloud platforms for enterprise access.

## REFERENCES

[1] Python Software Foundation. Python 3.10 Documentation. https://docs.python.org/3.10/ (Accessed: July 21, 2025).
[2] pandas Development Team. pandas: Python Data Analysis Library Documentation. https://pandas.pydata.org/ (Accessed: July 21, 2025).
[3] NumPy Developers. NumPy Reference Manual. https://numpy.org/doc/stable/ (Accessed: July 21, 2025).
[4] scikit-learn Developers. scikit-learn: Machine Learning in Python—User Guide & API. https://scikit-learn.org/stable/ (Accessed: July 21, 2025).
[5] Matplotlib Development Team. Matplotlib: Visualization with Python—Documentation. https://matplotlib.org/stable/ (Accessed: July 21, 2025).
[6] Seaborn Development Team. seaborn: Statistical Data Visualization in Python—Documentation. https://seaborn.pydata.org/ (Accessed: July 21, 2025).
[7] Streamlit Inc. Streamlit Documentation—Build Data Apps Quickly. https://docs.streamlit.io/ (Accessed: July 21, 2025).
[8] Taylor, S.J., Letham, B., et al. Prophet: Forecasting at Scale—Python Quick Start & Docs. https://facebook.github.io/prophet/ (Accessed: July 21, 2025).
[9] Joblib Contributors. Joblib: Lightweight Pipelines for Python—Documentation. https://joblib.readthedocs.io/ (Accessed: July 21, 2025).
[10] openpyxl Project. openpyxl: Python Library to Read/Write Excel 2010 xlsx/xlsm Files—Documentation. https://openpyxl.readthedocs.io/ (Accessed: July 21, 2025).
[11] Chen, D., Sain, S.L., & Guo, K. *Online Retail II Data Set. UCI Machine Learning Repository. https://archive.ics.uci.edu/ml/datasets/Online+Retail+II (Accessed: July 21, 2025).
[12] Kaggle Community. Telco Customer Churn Dataset. https://www.kaggle.com/blastchar/telco-customer-churn (Accessed: July 21, 2025).

[13] Kaggle Community. E-Commerce Behavior Data (2019 Oct–Nov): Multi-Category Online Store Events. https://www.kaggle.com/mkechinov/ecommerce-behavior-data-from-multi-category-store (Accessed: July 21, 2025).

[14] A DEEP PROBABILISTIC MODEL FOR CUSTOMER LIFETIME VALUE PREDICTION Xiaojing Wang, Tianqi Liu, Jingang Miaohttps://arxiv.org/pdf/1912.07753 (Accessed: July 21, 2025).

[15] Microsoft Power BI. https://learn.microsoft.com/en-us/power-bi/ (Accessed: July 21, 2025)

[16] Microsoft Power Query. https://learn.microsoft.com/en-us/power-query/ (Accessed: July 21, 2025)

[17] Microsoft Excel. https://support.microsoft.com/en-us/excel (Accessed: July 21, 2025)

## XI ANNEXURE

Following System architecture, Insights and  Actions' snippets enclosed:

Fig. 1 System architecture.

Fig. 2 Customer segmentation & Predicted CLTV based on  Churn risk insight & current CLTV.

Fig. 3 Customer segmentation & Churn probability with Revenue risk based on Churn risk insight.

Fig. 4 Customer promotion trigger (action) based on Hourly order pattern (insight).

Fig. 5  Customer promotion recommender (action) based on Customer RFM, CLTV & Churn (insight).

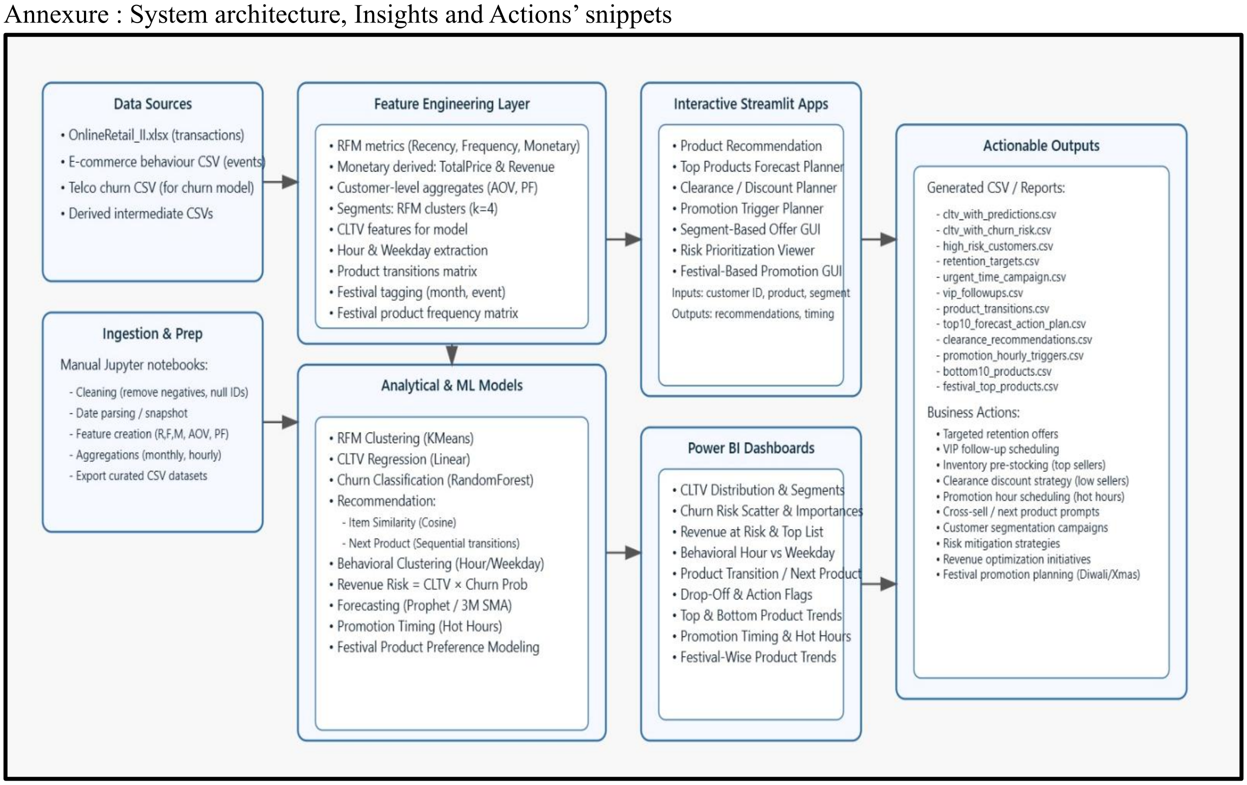
Fig. 6 Product Recommendation (action) based on Last purchase item (insight).

Fig. 7 Top Product Sale, Stock & Promotion month Forecast (action) based on Monthly sale value, qty. sold and no. of orders (insight)

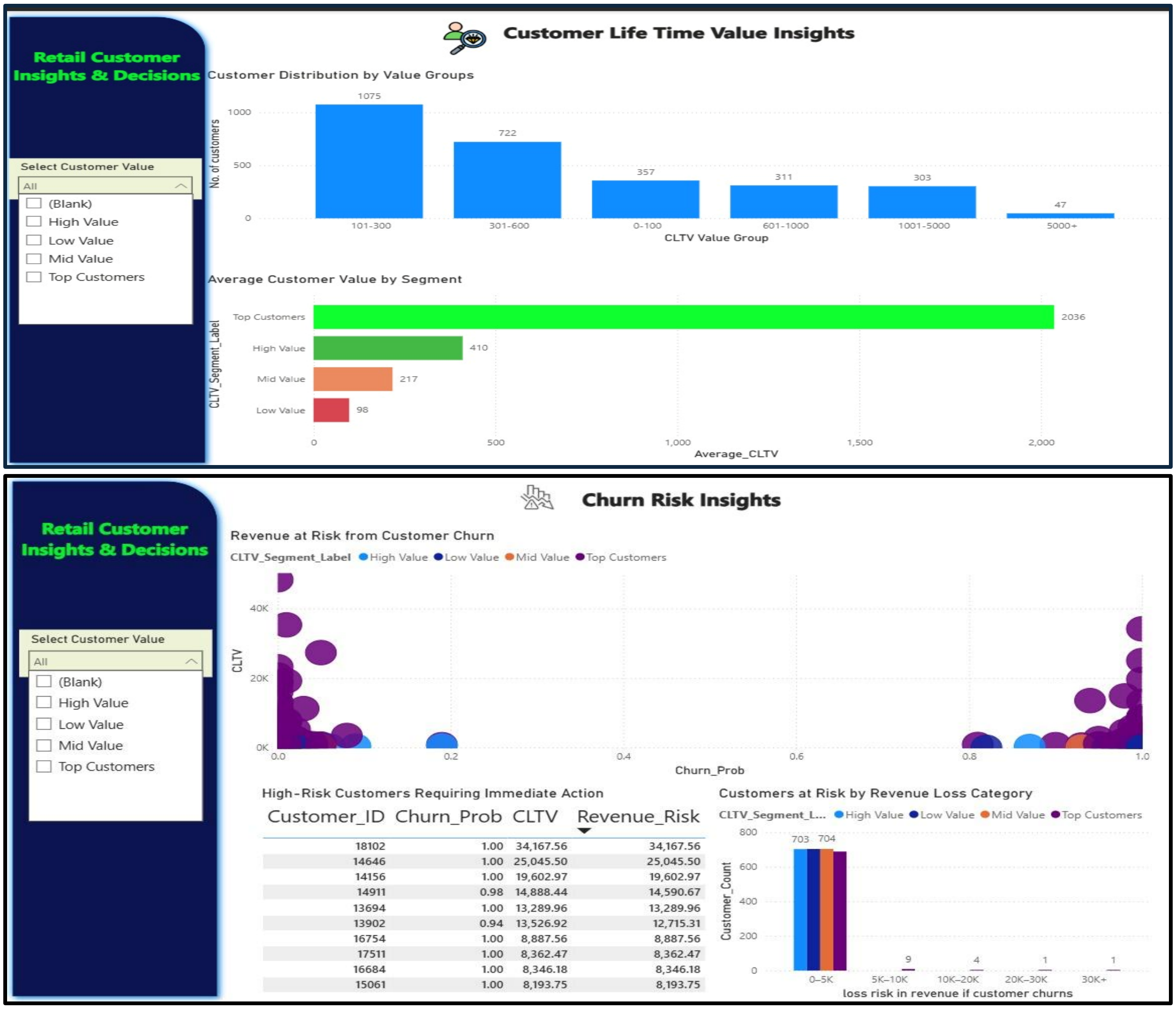
Fig. 8 Clearance sale planner (action) based on Products with ten lowest sale value and qty. sold (insight).

Fig. 9 Festival season Promotion planner (action) based on Product purchase historical data (insight).

Annexure : System architecture, Insights and Actions' snippets




*"Fig. 1" Retail business analysis & Strategic planning platform :  System architecture*




| Customer_ID | Churn_Prob | CLTV | Revenue_Risk |
|---|---|---|---|
| 18102 | 1.00 | 34,167.56 | 34,167.56 |
| 14646 | 1.00 | 25,045.50 | 25,045.50 |
| 14156 | 1.00 | 19,602.97 | 19,602.97 |
| 14911 | 0.98 | 14,888.44 | 14,590.67 |
| 13694 | 1.00 | 13,289.96 | 13,289.96 |
| 13902 | 0.94 | 13,526.92 | 12,715.31 |
| 16754 | 1.00 | 8,887.56 | 8,887.56 |
| 17511 | 1.00 | 8,362.47 | 8,362.47 |
| 16684 | 1.00 | 8,346.18 | 8,346.18 |
| 15061 | 1.00 | 8,193.75 | 8,193.75 |

| Customer_ID | Frequency | Recency | Monetary | AOV | PF | ProfitMargin | CLTV | CLTV_Segment | Predicted_CLTV |
|---|---|---|---|---|---|---|---|---|---|
| 12346 | 11 | 196 | 372.86 | 33.89636 | 0.056122 | 0.1 | 69.43566 | D | -0.544504146 |
| 12347 | 2 | 37 | 1323.32 | 661.66 | 0.054054 | 0.1 | 1305.437 | A | 1168.116575 |
| 12349 | 3 | 181 | 2671.14 | 890.38 | 0.016575 | 0.1 | 538.6553 | B | 1065.277486 |
| 12352 | 2 | 16 | 343.8 | 171.9 | 0.125 | 0.1 | 784.2938 | A | 1277.975342 |
| 12356 | 3 | 44 | 3562.25 | 1187.417 | 0.068182 | 0.1 | 2955.048 | A | 2201.316355 |
| 12358 | 3 | 356 | 2719.01 | 906.3367 | 0.008427 | 0.1 | 278.7749 | C | 931.2826781 |
| 12359 | 6 | 308 | 2563.36 | 427.2267 | 0.019481 | 0.1 | 303.7748 | B | 348.9610512 |
| 12360 | 5 | 276 | 1590.83 | 318.166 | 0.018116 | 0.1 | 210.3815 | C | 141.9161663 |
| 12361 | 3 | 220 | 321.35 | 107.1167 | 0.013636 | 0.1 | 53.31489 | D | -231.9935685 |
| 12369 | 3 | 228 | 1791.15 | 597.05 | 0.013158 | 0.1 | 286.7411 | C | 540.3320855 |
| 12370 | 3 | 44 | 774.62 | 258.2067 | 0.068182 | 0.1 | 642.5825 | A | 720.3063811 |
| 12371 | 3 | 235 | 2179.42 | 726.4733 | 0.012766 | 0.1 | 338.5057 | B | 739.4496214 |
| 12373 | 2 | 49 | 763.05 | 381.525 | 0.040816 | 0.1 | 568.3944 | B | 582.4424333 |
| 12374 | 3 | 166 | 2246.29 | 748.7633 | 0.018072 | 0.1 | 493.9132 | B | 862.7333425 |
| 12376 | 2 | 28 | 503.15 | 251.575 | 0.071429 | 0.1 | 655.892 | A | 757.2717374 |
| 12377 | 2 | 208 | 1798.2 | 899.1 | 0.009615 | 0.1 | 315.5495 | B | 937.9546365 |
| 12379 | 2 | 112 | 767.98 | 383.99 | 0.017857 | 0.1 | 250.2792 | C | 290.6558778 |
| 12380 | 7 | 197 | 6951.49 | 993.07 | 0.035533 | 0.1 | 1287.966 | A | 1674.14819 |
| 12388 | 2 | 136 | 1120.45 | 560.225 | 0.014706 | 0.1 | 300.709 | B | 511.3360569 |
| 12389 | 3 | 253 | 1433.33 | 477.7767 | 0.011858 | 0.1 | 206.7848 | C | 325.8344308 |
| 12391 | 5 | 198 | 2312.53 | 462.506 | 0.025253 | 0.1 | 426.2997 | B | 507.904295 |
| 12393 | 2 | 46 | 816.85 | 408.425 | 0.043478 | 0.1 | 648.1527 | A | 655.8795875 |
| 12395 | 4 | 231 | 2048.64 | 512.16 | 0.017316 | 0.1 | 323.7029 | B | 471.130759 |
| 12399 | 3 | 259 | 853.65 | 284.55 | 0.011583 | 0.1 | 120.302 | D | 12.45170587 |
| 12402 | 5 | 277 | 1031.3 | 206.26 | 0.018051 | 0.1 | 135.8933 | D | -55.5633203 |
| 12406 | 3 | 297 | 2975.06 | 991.6867 | 0.010101 | 0.1 | 365.6219 | B | 1108.30931 |

cltv_with_predictions

*"Fig. 2" Customer segmentation & Predicted CLTV based on Churn risk insight & current CLTV*

| Customer_ID | Frequency | Recency | Monetary | AOV | PF | ProfitMargin | CLTV | CLTV_Segment | Churn_Prob | Revenue_Risk |
|---|---|---|---|---|---|---|---|---|---|---|
| 12346 | 11 | 196 | 372.86 | 33.89636 | 0.056122 | 0.1 | 69.43566 | D | 0.98 | 68.04695 |
| 12347 | 2 | 37 | 1323.32 | 661.66 | 0.054054 | 0.1 | 1305.437 | A | 0 | 0 |
| 12349 | 3 | 181 | 2671.14 | 890.38 | 0.016575 | 0.1 | 538.6553 | B | 1 | 538.6553039 |
| 12352 | 2 | 16 | 343.8 | 171.9 | 0.125 | 0.1 | 784.2938 | A | 0 | 0 |
| 12356 | 3 | 44 | 3562.25 | 1187.417 | 0.068182 | 0.1 | 2955.048 | A | 0 | 0 |
| 12358 | 3 | 356 | 2719.01 | 906.3367 | 0.008427 | 0.1 | 278.7749 | C | 1 | 278.7749017 |
| 12359 | 6 | 308 | 2563.36 | 427.2267 | 0.019481 | 0.1 | 303.7748 | B | 1 | 303.7748052 |
| 12360 | 5 | 276 | 1590.83 | 318.166 | 0.018116 | 0.1 | 210.3815 | C | 1 | 210.3815036 |
| 12361 | 3 | 220 | 321.35 | 107.1167 | 0.013636 | 0.1 | 53.31489 | D | 1 | 53.31488636 |
| 12369 | 3 | 228 | 1791.15 | 597.05 | 0.013158 | 0.1 | 286.7411 | C | 1 | 286.7411184 |
| 12370 | 3 | 44 | 774.62 | 258.2067 | 0.068182 | 0.1 | 642.5825 | A | 0 | 0 |
| 12371 | 3 | 235 | 2179.42 | 726.4733 | 0.012766 | 0.1 | 338.5057 | B | 1 | 338.5056596 |
| 12373 | 2 | 49 | 763.05 | 381.525 | 0.040816 | 0.1 | 568.3944 | B | 0 | 0 |
| 12374 | 3 | 166 | 2246.29 | 748.7633 | 0.018072 | 0.1 | 493.9132 | B | 1 | 493.9131627 |
| 12376 | 2 | 28 | 503.15 | 251.575 | 0.071429 | 0.1 | 655.892 | A | 0 | 0 |
| 12377 | 2 | 208 | 1798.2 | 899.1 | 0.009615 | 0.1 | 315.5495 | B | 1 | 315.5495192 |
| 12379 | 2 | 112 | 767.98 | 383.99 | 0.017857 | 0.1 | 250.2792 | C | 1 | 250.2791964 |
| 12380 | 7 | 197 | 6951.49 | 993.07 | 0.035533 | 0.1 | 1287.966 | A | 1 | 1287.966421 |
| 12388 | 2 | 136 | 1120.45 | 560.225 | 0.014706 | 0.1 | 300.709 | B | 1 | 300.7090074 |
| 12389 | 3 | 253 | 1433.33 | 477.7767 | 0.011858 | 0.1 | 206.7848 | C | 1 | 206.7847628 |
| 12391 | 5 | 198 | 2312.53 | 462.506 | 0.025253 | 0.1 | 426.2997 | B | 1 | 426.2997222 |
| 12393 | 2 | 46 | 816.85 | 408.425 | 0.043478 | 0.1 | 648.1527 | A | 0 | 0 |
| 12395 | 4 | 231 | 2048.64 | 512.16 | 0.017316 | 0.1 | 323.7029 | B | 1 | 323.7028571 |
| 12399 | 3 | 259 | 853.65 | 284.55 | 0.011583 | 0.1 | 120.302 | D | 1 | 120.302027 |
| 12402 | 5 | 277 | 1031.3 | 206.26 | 0.018051 | 0.1 | 135.8933 | D | 1 | 135.8933213 |
| 12406 | 3 | 297 | 2975.06 | 991.6867 | 0.010101 | 0.1 | 365.6219 | B | 1 | 365.6218519 |

*"Fig. 3" Customer segmentation & Churn probability with Revenue risk based on Churn risk insight*

| CLTV_Segment_Label | Hour | Total_Orders | Total_Revenue | Trigger_Class |
|---|---|---|---|---|
| A | 7 | 31 | 1344.84 | COLD_HOUR |
| A | 8 | 182 | 10952.25 | COLD_HOUR |
| A | 9 | 505 | 33605.22 | WARM_HOUR |
| A | 10 | 900 | 54116.012 | WARM_HOUR |
| A | 11 | 966 | 74449.311 | HOT_HOUR |
| A | 12 | 1253 | 88838.68 | HOT_HOUR |
| A | 13 | 1100 | 81296.94 | HOT_HOUR |
| A | 14 | 870 | 73473.85 | WARM_HOUR |
| A | 15 | 717 | 55425.74 | WARM_HOUR |
| A | 16 | 451 | 53428.36 | COLD_HOUR |
| A | 17 | 236 | 19156.341 | COLD_HOUR |
| A | 18 | 100 | 5555.88 | COLD_HOUR |
| A | 19 | 50 | 3784.58 | COLD_HOUR |
| A | 20 | 12 | 959.75 | COLD_HOUR |
| B | 7 | 7 | 231.37 | COLD_HOUR |
| B | 8 | 100 | 5076.71 | COLD_HOUR |
| B | 9 | 275 | 14242.43 | COLD_HOUR |
| B | 10 | 565 | 33867.16 | WARM_HOUR |
| B | 11 | 533 | 37317.002 | WARM_HOUR |
| B | 12 | 692 | 52167.451 | HOT_HOUR |
| B | 13 | 638 | 46042.171 | HOT_HOUR |
| B | 14 | 583 | 43440.84 | HOT_HOUR |
| B | 15 | 522 | 32680.371 | WARM_HOUR |
| B | 16 | 312 | 22757.03 | WARM_HOUR |
| B | 17 | 144 | 9409.49 | COLD_HOUR |
| B | 18 | 63 | 3186.83 | COLD_HOUR |

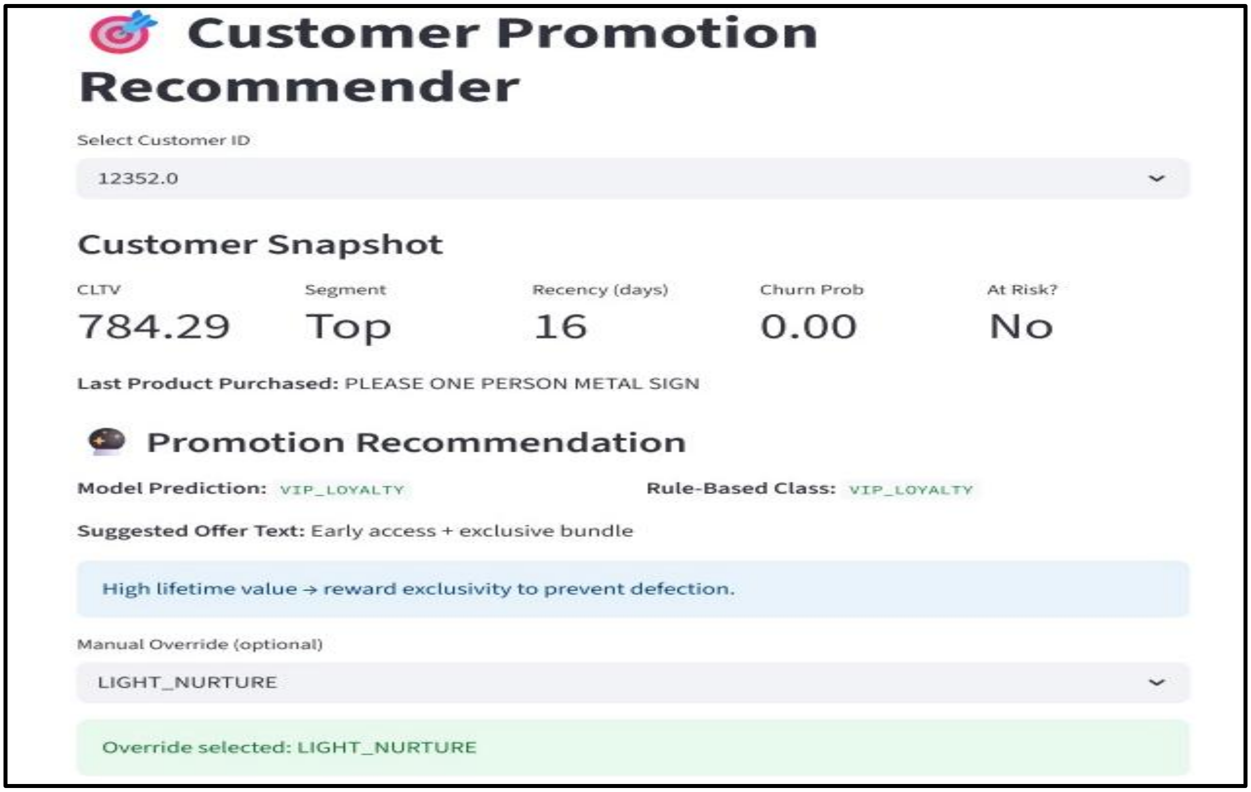
promotion_hourly_triggers

*"Fig. 4" Customer promotion trigger (action) based on Hourly order pattern (insight)*

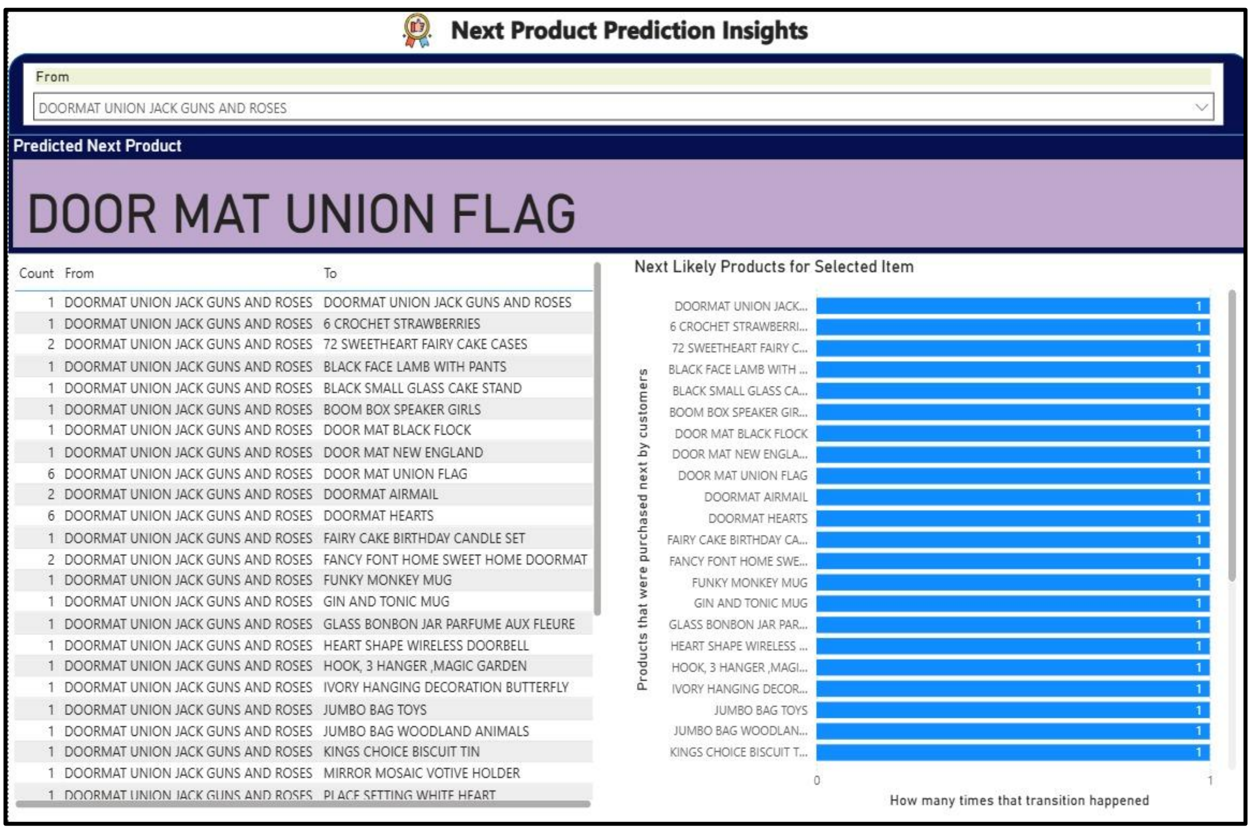
**INSIGHT : CUSTOMER PROMOTION DATASET BASED ON LAST PURCHASE**

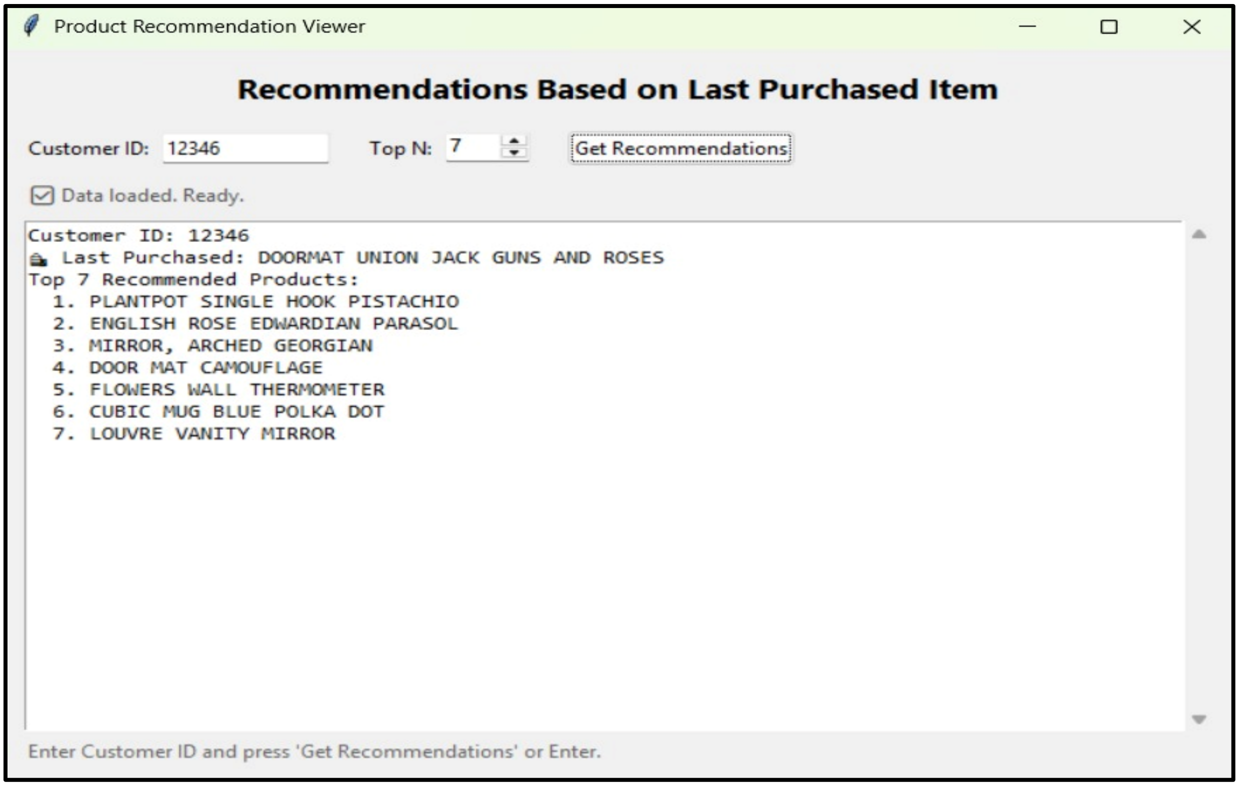
| Frequency | Recency | Monetary | AOV | PF | Profit Margin | CLTV | CLTV_Segment | Predicted_ | Churn_Prob | Last_Purchase_Date | Last_Product | Days_Since_Last_Purchase | CLTV_Segment_Label | Value_Tier | At_Risk | Promotion_Class | Suggested_Offer_Text |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 11 | 196 | 372.86 | 33.90 | 0.06 | 0.1 | 69.44 | D | -0.54 | 0.98 | 28-06-2010 13:53 | DOORMAT UNION FLAG | 165 | D | Low | 1 | WINBACK | Reactivate: 20% comeback code |
| 2 | 37 | 1323.32 | 661.66 | 0.05 | 0.1 | 1305.44 | A | 1168.12 | 0 | 07-12-2010 14:57 | COLOUR GLASS. STAR T-LIGHT | 3 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 3 | 181 | 2671.14 | 890.38 | 0.02 | 0.1 | 538.66 | B | 1065.28 | 1 | 28-10-2010 08:23 | DOORMAT WELCOME PUPPIE | 43 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 2 | 16 | 343.80 | 171.90 | 0.13 | 0.1 | 784.29 | A | 1277.98 | 0 | 29-11-2010 10:07 | PLEASE ONE PERSON METAL S | 11 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 3 | 44 | 3562.25 | 1187.42 | 0.07 | 0.1 | 2955.05 | A | 2201.32 | 0 | 24-11-2010 12:24 | RED RETROSPOT CAKE STAND | 16 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 3 | 356 | 2719.01 | 906.34 | 0.01 | 0.1 | 278.77 | C | 931.28 | 1 | 29-11-2010 10:56 | EDWARDIAN PARASOL NATUR | 11 | C | Medium | 1 | MID_SAVE | Limited 10% coupon + loyalty enr |
| 6 | 308 | 2563.36 | 427.23 | 0.02 | 0.1 | 303.77 | B | 348.96 | 1 | 10-10-2010 11:16 | TOAST ITS - HAPPY BIRTHDAY | 61 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 5 | 276 | 1590.83 | 318.17 | 0.02 | 0.1 | 210.38 | C | 141.92 | 1 | 25-11-2010 11:04 | POSTAGE | 15 | C | Medium | 1 | MID_SAVE | Limited 10% coupon + loyalty enr |
| 3 | 220 | 321.35 | 107.12 | 0.01 | 0.1 | 53.31 | D | -231.99 | 1 | 03-09-2010 15:19 | LUNCH BAG PINK RETROSPOT | 98 | D | Low | 1 | WINBACK | Reactivate: 20% comeback code |
| 3 | 228 | 1791.15 | 597.05 | 0.01 | 0.1 | 286.74 | C | 540.33 | 1 | 22-10-2010 13:13 | RED HANGING HEART T-LIGHT | 49 | C | Medium | 1 | MID_SAVE | Limited 10% coupon + loyalty enr |
| 3 | 44 | 774.62 | 258.21 | 0.07 | 0.1 | 642.58 | A | 720.31 | 0 | 25-03-2010 12:10 | POSTAGE | 260 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 3 | 235 | 2179.42 | 726.47 | 0.01 | 0.1 | 338.51 | B | 739.45 | 1 | 26-10-2010 13:37 | ALARM CLOCK BAKELIKE GREE | 45 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 2 | 49 | 763.05 | 381.53 | 0.04 | 0.1 | 568.39 | B | 582.44 | 0 | 25-03-2010 13:49 | RETRO SPOT MUG | 260 | B | High | 0 | UPSWING_UPSEL | Bundle offer on premium related |
| 3 | 166 | 2246.29 | 748.76 | 0.02 | 0.1 | 493.91 | B | 862.73 | 1 | 14-10-2010 13:31 | POSTAGE | 57 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 2 | 28 | 503.15 | 251.58 | 0.07 | 0.1 | 655.89 | A | 757.27 | 0 | 15-11-2010 12:15 | POSTAGE | 25 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 2 | 208 | 1798.20 | 899.10 | 0.01 | 0.1 | 315.55 | B | 937.95 | 1 | 23-11-2010 19:24 | RETROSPOT TEA SET CERAMIC | 17 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 2 | 112 | 767.98 | 383.99 | 0.02 | 0.1 | 250.28 | C | 290.66 | 1 | 13-10-2010 14:46 | PLASTERS IN TIN WOODLAND | 58 | C | Medium | 1 | MID_SAVE | Limited 10% coupon + loyalty enr |
| 7 | 197 | 6951.49 | 993.07 | 0.04 | 0.1 | 1287.97 | A | 1674.15 | 1 | 31-08-2010 14:54 | SPACEBOY LUNCH BOX | 101 | A | Top | 1 | VIP_LOYALTY | Early access + exclusive bundle |
| 2 | 136 | 1120.45 | 560.23 | 0.01 | 0.1 | 300.71 | B | 511.34 | 1 | 20-09-2010 12:41 | NOEL WOODEN BLOCK LETTE | 81 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 3 | 253 | 1433.33 | 477.78 | 0.01 | 0.1 | 206.78 | C | 325.83 | 1 | 02-11-2010 11:52 | MAGNETS PACK OF 4 HOME S | 38 | C | Medium | 1 | MID_SAVE | Limited 10% coupon + loyalty enr |
| 5 | 198 | 2312.53 | 462.51 | 0.03 | 0.1 | 426.30 | B | 507.90 | 1 | 01-09-2010 12:38 | HEART OF WICKER SMALL | 100 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |
| 2 | 46 | 816.85 | 408.43 | 0.04 | 0.1 | 648.15 | A | 655.88 | 0 | 22-11-2010 16:10 | LUNCH BAG BLACK SKULL. | 18 | A | Top | 0 | VIP_LOYALTY | Early access + exclusive bundle |
| 4 | 231 | 2048.64 | 512.16 | 0.02 | 0.1 | 323.70 | B | 471.13 | 1 | 03-12-2010 16:35 | PACK OF 60 DINOSAUR CAKE C | 7 | B | High | 1 | HIGH_VALUE_SAV | Personalized 15% retention vouch |

promotion_dataset

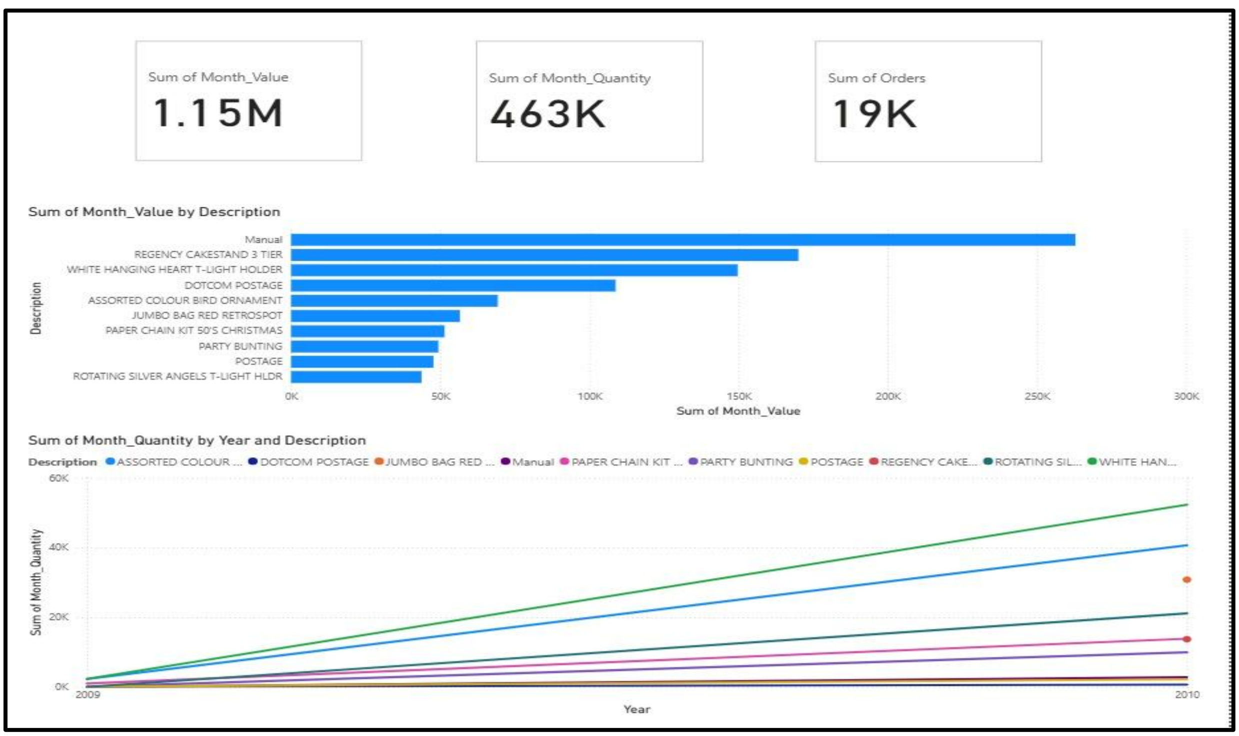


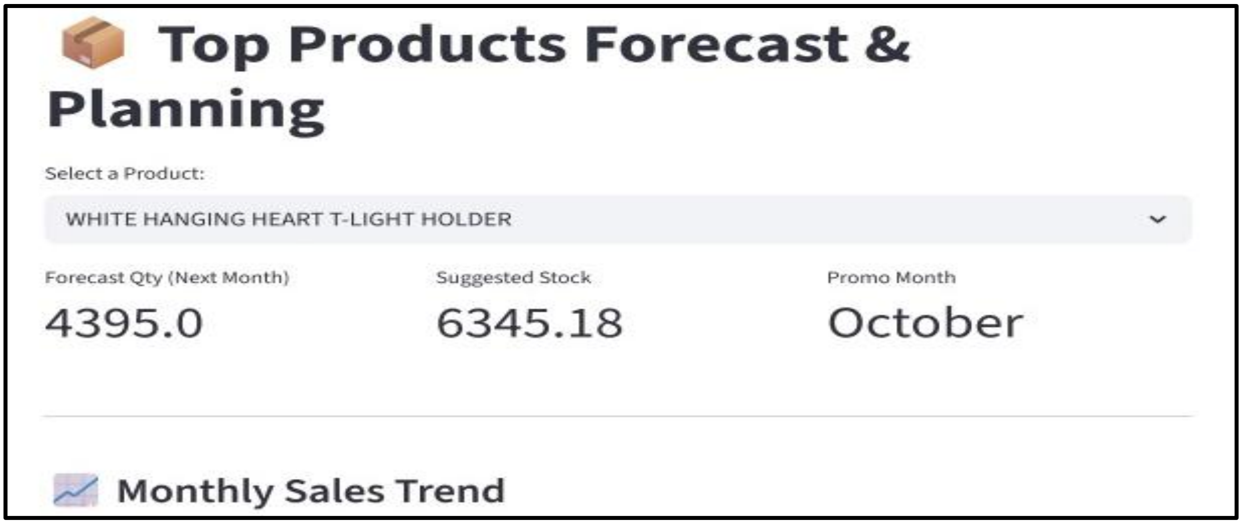

*"Fig. 5" Customer promotion recommender (action) based on Customer RFM, CLTV & Churn (insight)*

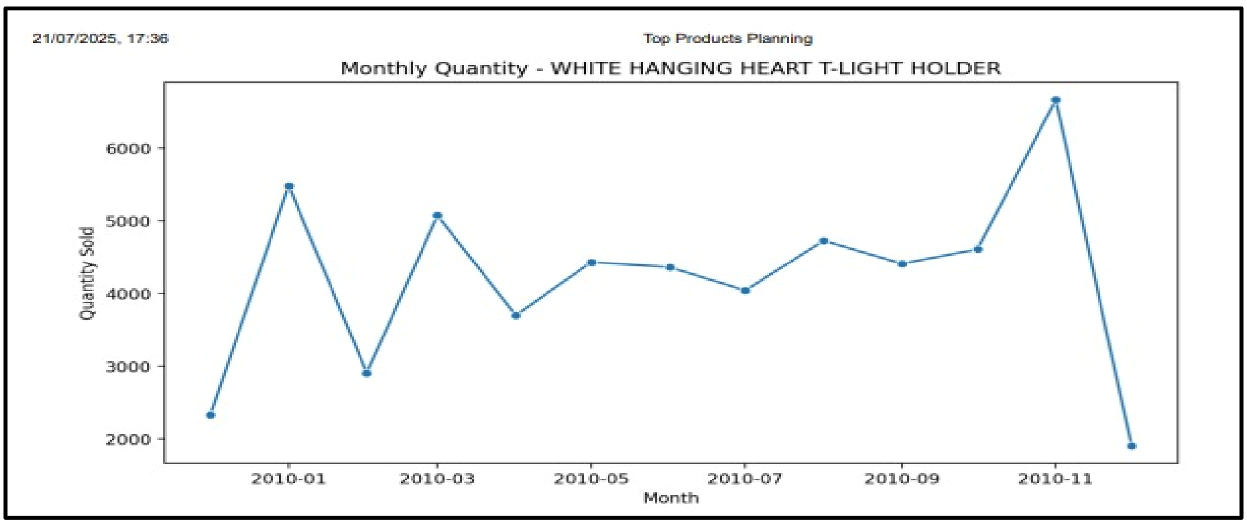




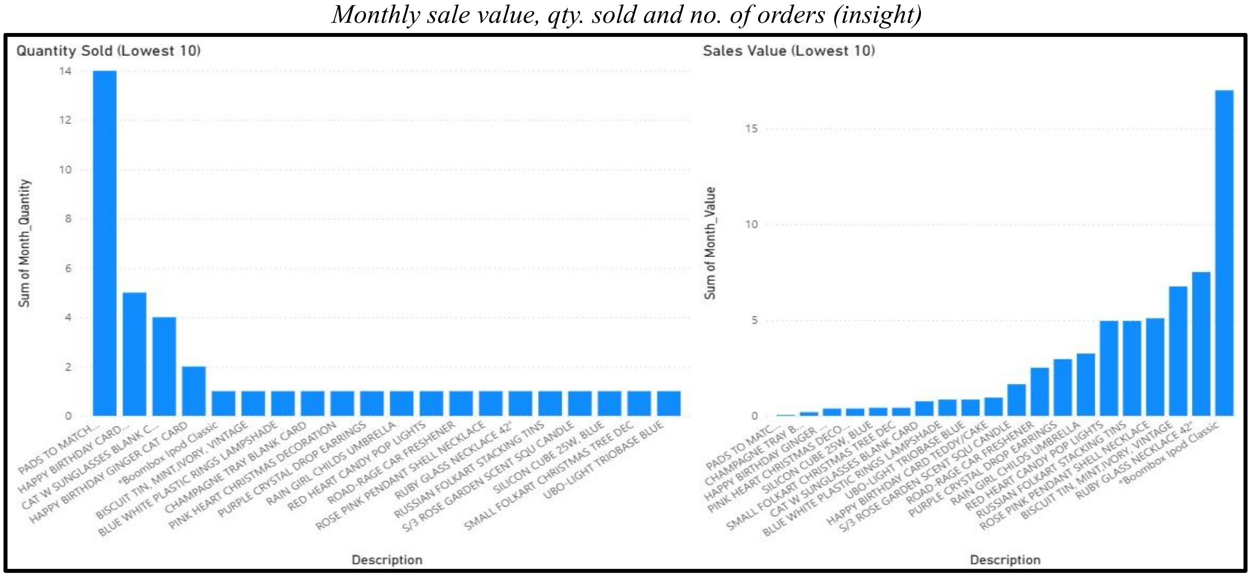

*"Fig. 6" Product Recommendation (action) based on Last purchase item (insight)*

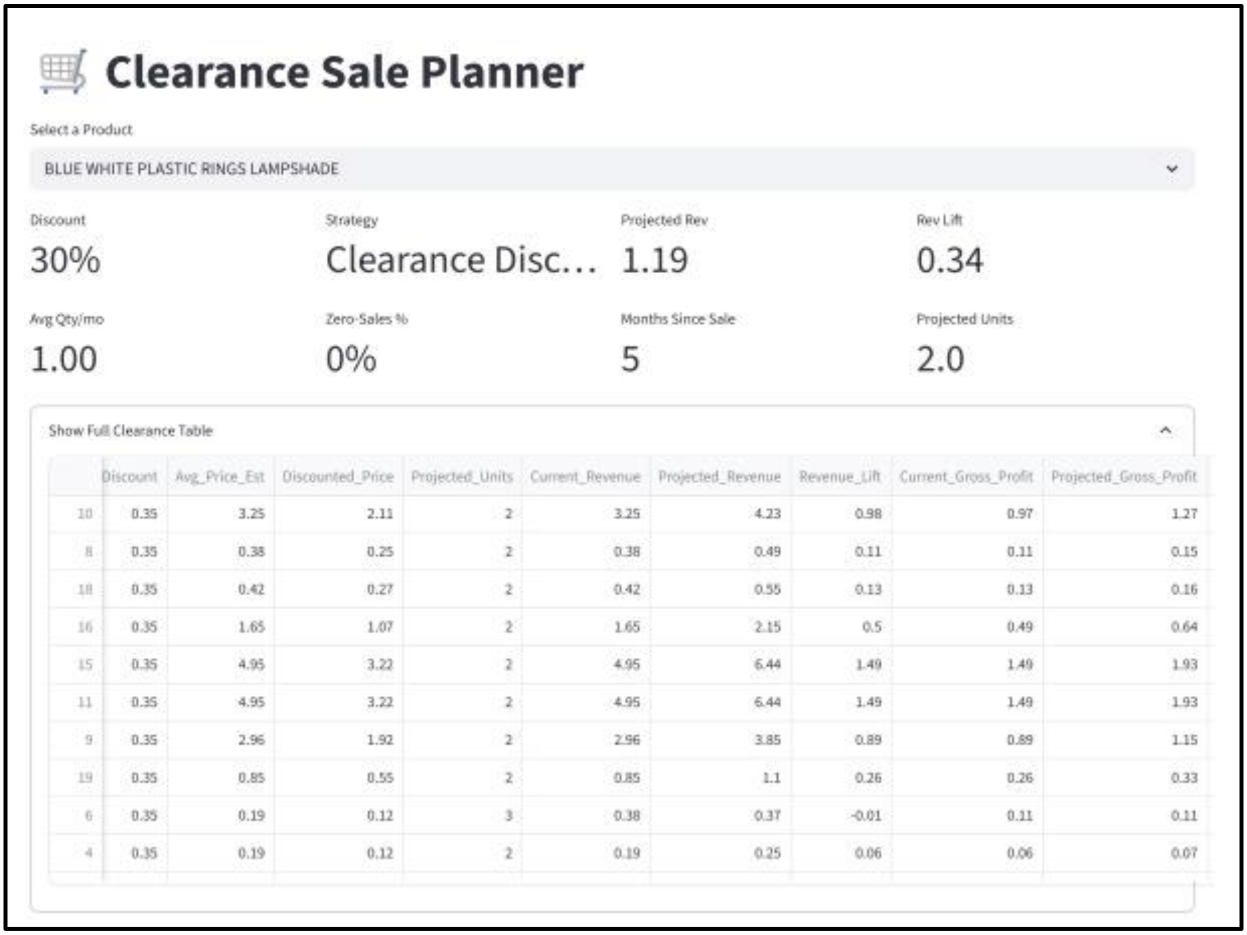




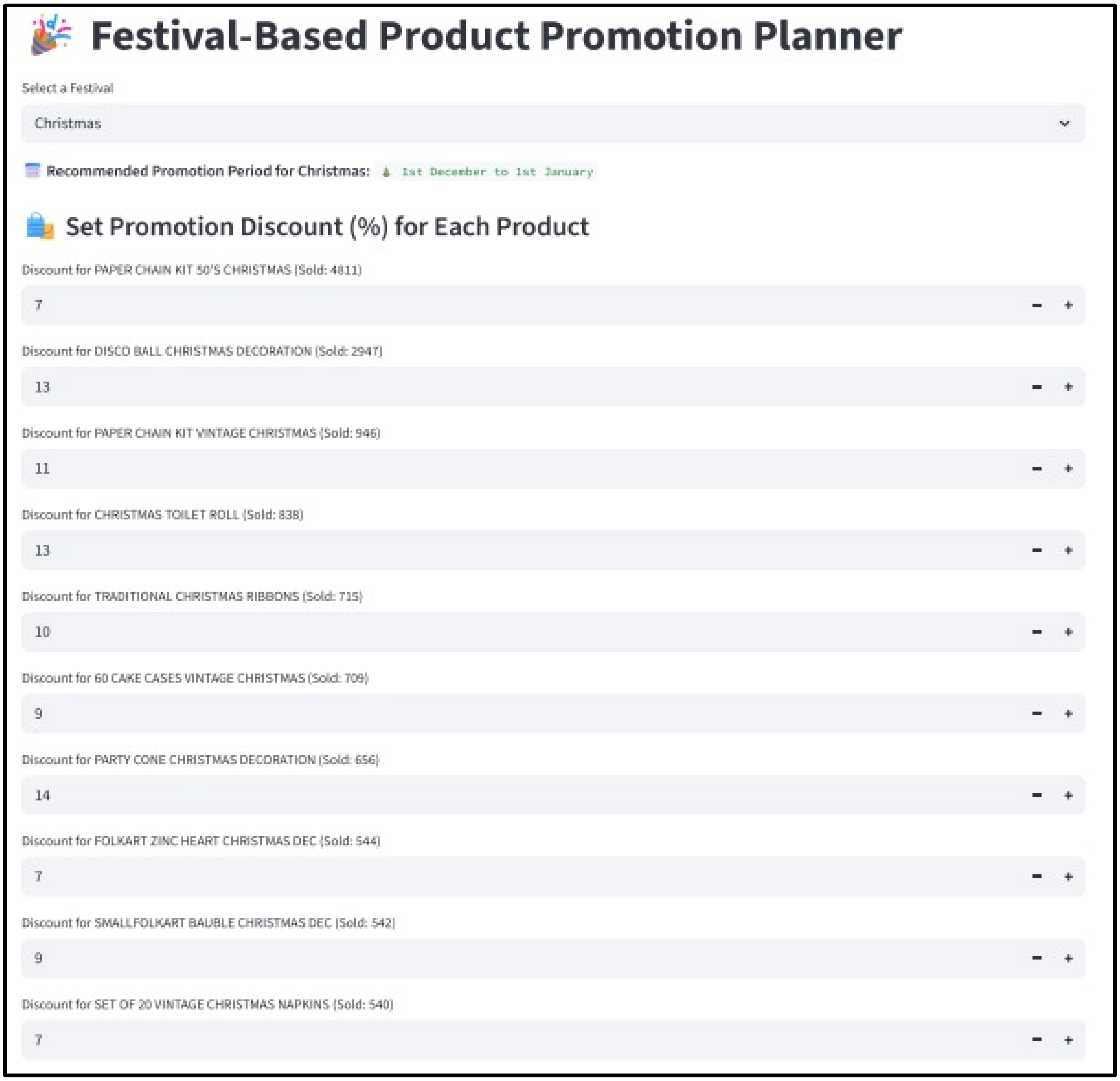

*"Fig. 7" Top Product Sale, Stock & Promotion month Forecast (action) based on Monthly sale value, qty. sold and no. of orders (insight)*






| | Discount | Avg_Price_Est | Discounted_Price | Projected_Units | Current_Revenue | Projected_Revenue | Revenue_Lift | Current_Gross_Profit | Projected_Gross_Profit |
|---|---|---|---|---|---|---|---|---|---|
| 10 | 0.35 | 3.25 | 2.11 | 2 | 3.25 | 4.23 | 0.98 | 0.97 | 1.27 |
| 8 | 0.35 | 0.38 | 0.25 | 2 | 0.38 | 0.49 | 0.11 | 0.11 | 0.15 |
| 18 | 0.35 | 0.42 | 0.27 | 2 | 0.42 | 0.55 | 0.13 | 0.13 | 0.16 |
| 16 | 0.35 | 1.65 | 1.07 | 2 | 1.65 | 2.15 | 0.5 | 0.49 | 0.64 |
| 15 | 0.35 | 4.95 | 3.22 | 2 | 4.95 | 6.44 | 1.49 | 1.49 | 1.93 |
| 11 | 0.35 | 4.95 | 3.22 | 2 | 4.95 | 6.44 | 1.49 | 1.49 | 1.93 |
| 9 | 0.35 | 2.96 | 1.92 | 2 | 2.96 | 3.85 | 0.89 | 0.89 | 1.15 |
| 19 | 0.35 | 0.85 | 0.55 | 2 | 0.85 | 1.1 | 0.26 | 0.26 | 0.33 |
| 6 | 0.35 | 0.19 | 0.12 | 3 | 0.38 | 0.37 | -0.01 | 0.11 | 0.11 |
| 4 | 0.35 | 0.19 | 0.12 | 2 | 0.19 | 0.25 | 0.06 | 0.06 | 0.07 |

*"Fig. 8" Clearance sale planner (action) based on Products with ten lowest sale value and qty. sold (insight)*




*"Fig. 9" Festival season Promotion planner (action) based on Product purchase historical data (insight)*