Technical paper for Retail business analysis & 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

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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.

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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

A diagram of a retail customer intelligence platform

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

A graph showing a customer value

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

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

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

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A screenshot of a customer review

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

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

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A graph showing a line of heart flight holders

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*“Fig. 7” Top Product Sale, Stock & Promotion month Forecast (action) based on*

*Monthly sale value, qty. sold and no. of orders (insight)*

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A screenshot of a sales report

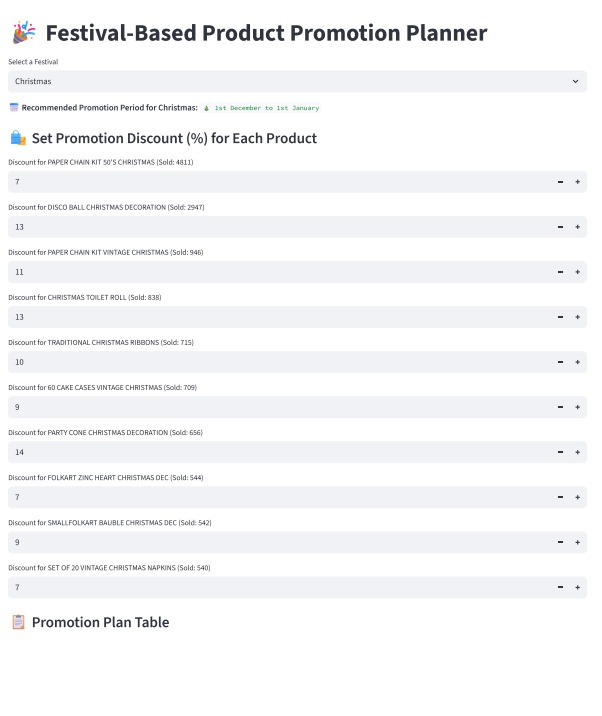
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*“Fig. 8” Clearance sale planner (action) based on*

*Products with ten lowest sale value and qty. sold (insight)*

A graph showing a sales increase

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*“Fig. 9” Festival season Promotion planner (action) based on*

*Product purchase historical data (insight)*