AI-Powered Personalized Recommendation System for Electronics E-Commerce

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***Abstract*—The growth in e-commerce necessitates highly personalized customer experiences to sustain interest and loyalty. This study recommends an AI-driven hybrid recommendation system for electronics e-commerce platforms. Based on the Retailrocket Recommender System Dataset, the solution utilizes content-based and collaborative filtering strategies to deliver precise, real-time product suggestions. A dynamic analytics dashboard is also part of the system, giving actionable insights for inventory control, upselling, and cross-selling strategies. With scalable AI methods, the software has its eyes on enhancing customer satisfaction, optimizing marketing campaigns, boosting organizational revenues, and optimizing customer retention.**

***Index Terms*—E-Commerce, Recommendation system, Customer Satisfaction**

I. Introduction

In today's competitive e-commerce landscape, individualized product suggestions are the driving force of customer engagement, conversion rates, and brand loyalty. Shoppers expect more customized shopping experiences with less burden of too many off-theme offerings. Recommender systems have thus become integral parts of successful e-commerce websites.

This project is designed to develop an item-based collaborative filtering recommendation system for electronics e-commerce, in which technical specifications and product variety are bound to complicate the decision-making process. The system, based on the RocketRetail Recommender System Dataset, provides recommendations from previous user-item interaction patterns based on cosine similarity to identify similar items.

A live Streamlit application has been built to offer product suggestions, show customer activity on an EDA dashboard, and identify top trends. This end-to-end system not only improves customer satisfaction with better personalization but also provides actionable insights for upselling campaigns, inventory optimization, and customer loyalty programs.

By combining scalable data processing techniques with an interactive web-based interface, the project provides a realistic approach towards building real-time personalized recommendation systems for modern-day e-commerce websites.

A. Problem Statement

The retail e-commerce business of consumer electronics is expanding rapidly, offering customers a wide range of products and personalized services. The surplus, however, results in decision fatigue, wherein users find it hard to select pertinent products due to too many options and non-personalized recommendations. High rates of user engagement do not convert into actual conversions, indicating that users' interests and suggested products are not aligned.

Existing recommendation systems tend to overlook providing the right, real-time recommendations due to shifting user activity, resulting in missed sales opportunities, low customer satisfaction, and inefficient inventory management. There is a crucial need for a high-scale, real-time collaborative filtering-based recommendation system to ensure an effective match between users and products they are most interested in and most likely to take action upon.

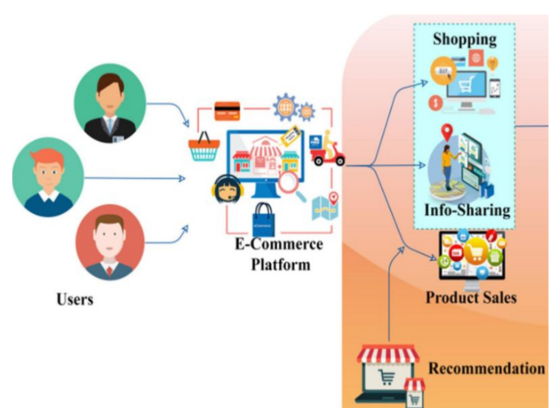


Fig. 1. Proposed model (8)

B. Objective

The primary objective of this project is to create a personalized item-based collaborative filtering recommendation system for online e-commerce stores selling electronics. The system aims to:

- Make predictions about user preference from the previous user-item interaction records of the RocketRetail dataset.
- Provide real-time personalized product suggestions by implementing item-based collaborative filtering based on cosine similarity.
- Enable cross-selling and upselling features through personalized recommendation flows.
- Deliver real-time customer behavior visualization, trending item analysis, and an actionable business insights analytics dashboard.
- Enhance customer experience by removing decision fatigue, promoting product discovery, and enhancing conversion and retention.

II. LITERATURE REVIEW

A. Collaborative Filtering Content-Based Recommendation Systems -

Recommendation algorithms have developed into vital components of contemporary e-commerce platforms, allowing companies to better engage users and predict client wants. According to Sarwar et al. (2001), collaborative filtering (CF) is based on determining connections between users or objects by looking at past interactions. There are two primary techniques to CF: item-based CF, which suggests similar items to users based on their past behavior, and user-based CF, which finds similar people to suggest new items. Although collaborative filtering is a potent technique for revealing latent preferences, it frequently runs into issues like data sparsity and cold-start issues, where the efficacy of recommendations is limited by a lack of interaction data.

Some of these restrictions are addressed by Content-Based Filtering (CBF), which suggests goods with features that are comparable to those a user has already interacted with. CBF focuses on matching user profiles with product metadata, including product kind, brand, characteristics, and pricing. While CBF might help customers avoid cold starts, it can also result in overspecialization, where users are not exposed to new product categories and recommendations lack diversity. Because of their capacity to strike a balance between relevance, originality, and coverage—thereby attaining higher recommendation accuracy and user satisfaction—hybrid techniques that combine CF and CBF have gained popularity. According to studies by Burke (2002), hybrid models routinely perform better than separate CF or CBF approaches in a variety of fields, such as media recommendation and e-commerce.

Singular Value Decomposition (SVD) and Alternating Least Squares (ALS) are two matrix factorization techniques that have been frequently employed in recent years to enhance collaborative filtering models. Even with little interaction data, these methods aid in collecting latent factors between users and items, allowing for more precise predictions. Recommendation systems have been further improved by deep learning models, such as Neural Collaborative Filtering, which represent intricate nonlinear interactions between users and items. (2)

B. AI-Driven Personalization in E-Commerce -

In the digital economy, artificial intelligence has drastically changed personalization tactics, allowing companies to provide incredibly customized client experiences. E-commerce platforms can evaluate vast amounts of interaction data, learn changing user patterns, and produce dynamic, real-time suggestions thanks to sophisticated machine learning algorithms. Smith points out that Amazon's AI-powered recommendation engine accounts for about 35% of their income, highlighting the enormous commercial potential of tailored recommendations. Through consumer segmentation, future purchase behavior prediction, and marketing strategy optimization, contemporary AI models go beyond simple recommendations. While predictive models like Random Forests and Gradient Boosted Trees are frequently used to foresee consumer actions, techniques like clustering algorithms (e.g., K-means) assist firms in grouping customers based on behavioral patterns.

To improve recommendation systems based on real-time user feedback, reinforcement learning has become a potent tool in addition to supervised learning techniques. Reinforcement learning makes recommendations more sustainable and user-centric by concentrating on optimizing long-term user engagement rather than just generating transient clicks or sales. Additionally, companies can experimentally assess new customization methods using A/B testing approaches, and predictive strategic planning is made possible by trend analysis. This project intends to create a highly intelligent and adaptive recommendation system that not only improves the shopping experience but also offers practical insights to boost revenue development, customer retention, and business decision-making by incorporating these state-of-the-art AI methodologies. (1)

III. PROPOSED WORK

A. Survey Summary

To collect data on shopping behavior and affinity when shopping electronics online, an online survey through Google Forms was carried out. Through the survey, opinions were sought across different demographics, focusing on shopping frequency, brand influences, and purchasing behavior to guide recommendation system design.

Key Metrics -

- Age Segments: 18-35 years old are most electronics shoppers.
- Shopping Frequency: Most are occasional shoppers; there is a smaller segment than shops regularly.
- Purchase Drivers: Price, promotions, and brand are predominant drivers.

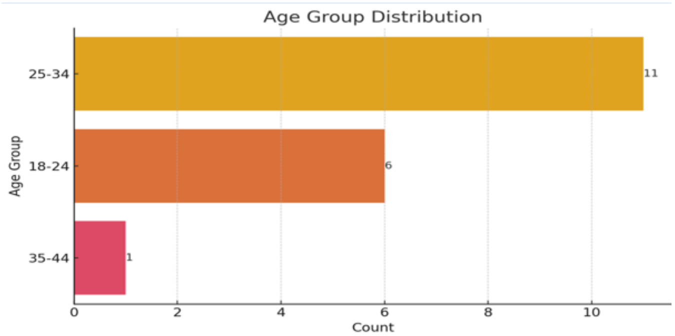


Fig. 2. Age Group Distribution

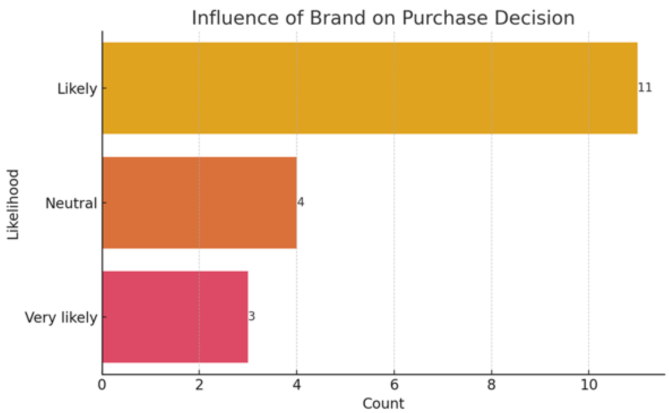


Fig. 3. Influence of Brand on Purchase Decision

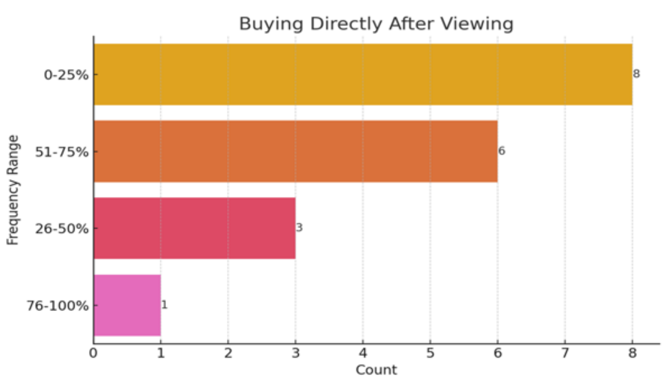


Fig. 4. Buying directly after viewing

- Behavioral Patterns: 75% of customers add to cart and purchase later, reflecting a blend of planned and impulse behavior.
- Comfort with AI: Overwhelmingly, they embrace AI-driven product recommendations.

Survey Insights and Data Analysis-

- Demographic Trends: 18–35 age group is most receptive towards AI-driven personalized shopping experiences and hence emerges as a best target audience.
- Decision-Making Behavior: Purchase behavior sees high engagement levels to promotion and offers, while longer cart purchasing duration suggests zones of prospective AI retargeting opportunity.
- Brand Loyalty: Brand trust remains a key purchase driver, and brand recommendation personalization must thus be required.
- Conversion Gaps: Retailrocket event logs comparison finds huge drop from view to transaction completion, which implies the need for personalized interaction methods.
- Peak Usage Times: Users are most engaged in late evening and early morning times, ideal for sending AI-driven recommendation nudges.
- Strategic Implication: Study findings validate that behavior-aware, AI-driven recommendation platforms can dramatically improve engagement rates, conversions, and customer retention for electronics e-commerce.

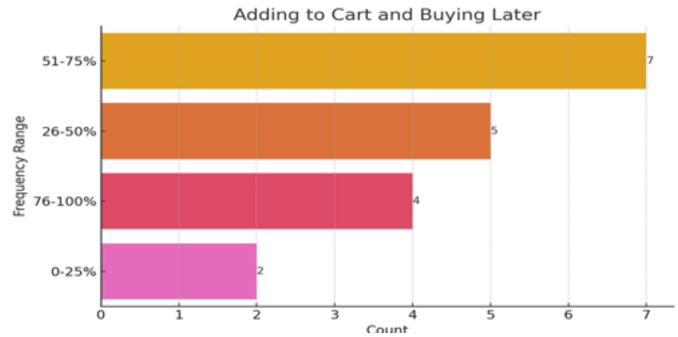


Fig. 5. Adding to Cart and Buying Later

B. Architecture of Hybrid Recommendation System

The architecture of a hybrid recommendation system created with the Retailrocket dataset is depicted in the framework that is being presented. To improve inventory management and user engagement, the system incorporates a number of recommendation techniques.

The main source of data is the Retailrocket dataset, which includes user activity, product details, and past purchases.

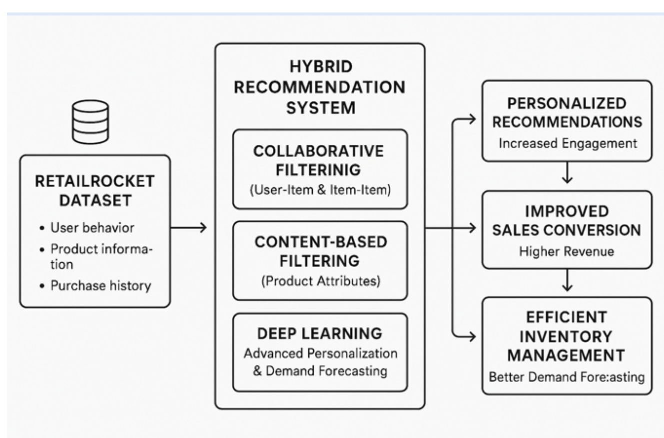


Fig. 6. Architecture of Hybrid Recommendation System

Three fundamental methods are combined in a hybrid recommendation system that uses this data:

- Collaborative Filtering (interactions between items and users)
- Filtering based on content (using product qualities)
- Deep Learning models (for demand forecasting and more sophisticated customisation).

The system may produce personalized recommendations thanks to the hybrid method, which raises user engagement.

Consequently, companies can attain higher revenue through improved sales conversion.

Additionally, improved demand forecasting facilitates Efficient Inventory Management, which in turn promotes more precise demand forecasting and lessens stock-related problems.

IV. METHODOLOGY

A. Data Collection and Pre-Processing

The project utilized the Retailrocket Recommender System Dataset, comprising four main datasets:

- events
- item properties part 1
- item properties part 2
- category tree

Data preprocessing was conducted using Pandas and NumPy libraries.

1) Key preprocessing steps included::

- Handling missing values and duplicates.
- Merging item properties datasets and associating items with electronics categories.
- Encoding categorical identifiers (visitor IDs, item IDs) using LabelEncoder for efficient computation.
- Constructing clean datasets focused exclusively on electronics transactions to tailor the recommendation system.

B. Exploratory Data Analysis (EDA)

An extensive EDA was performed to understand customer behavior patterns using Streamlit and Matplotlib. Key EDA findings included:

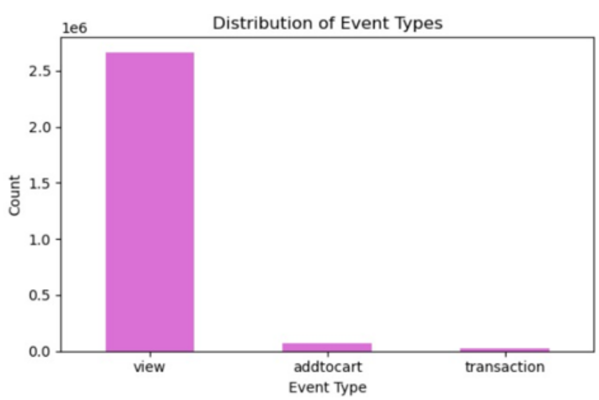


Fig. 7. Distribution of Event Types

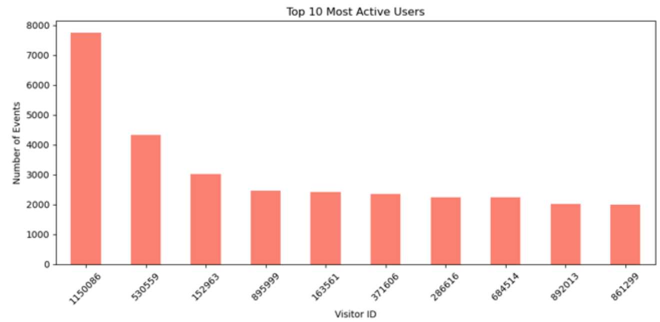


Fig. 8. Most Active Users

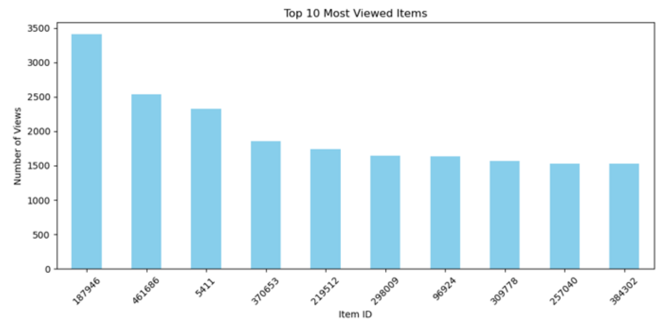


Fig. 9. Top 10 viewed items

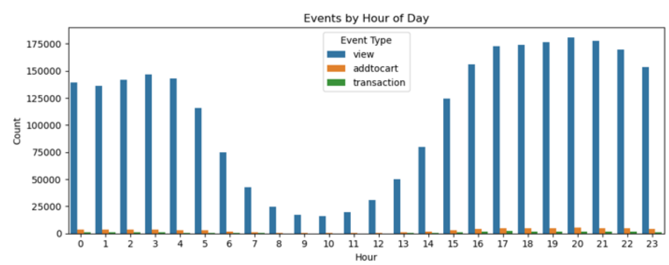


Fig. 10. Events by hour of day

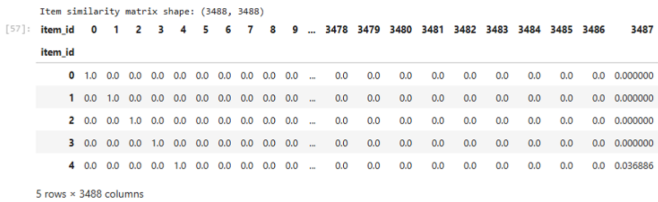
- Distribution of events (view, add-to-cart, transaction).
- Identification of top viewed items and most active users.
- Analysis of conversion gaps between product views and completed purchases.
- Peak times of user engagement identified as late evenings and early mornings.

These insights informed the model development phase by revealing user preferences and interaction trends.

C. Model Development (Collaborative Filtering)

The recommendation engine was developed using Item-Based Collaborative Filtering with Cosine Similarity. The model building steps included:

- Creating a user-item interaction matrix capturing historical events.
- Computing pairwise cosine similarity between items to build an item-item similarity matrix.



Item similarity matrix shape: (3488, 3488)

item_id	0	1	2	3	4	5	6	7	8	9	...	3478	3479	3480	3481	3482	3483	3484	3485	3486	3487
item_id																					
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000
1	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000
2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000
3	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000
4	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.036886

5 rows × 3488 columns

Fig. 11. Similarity Matrix

- For each user, generating top N recommendations by selecting items most similar to those they interacted with previously.

Memory-based collaborative filtering was chosen over more complex deep learning models to prioritize scalability, simplicity, and real-time response needs.

D. Insights Extraction

The model outputs were enriched by behavioral analysis:

- High cart abandonment rates indicated opportunities for retargeting.
- Brand and offer sensitivity suggested dynamic recommendation possibilities based on ongoing promotions.
- Identification of trending items based on real-time event streams enabled timely recommendations aligned with user interests.

E. Deployment and Real-Time Personalization

A full-stack solution was deployed using Streamlit, enabling real-time recommendations and analytics.

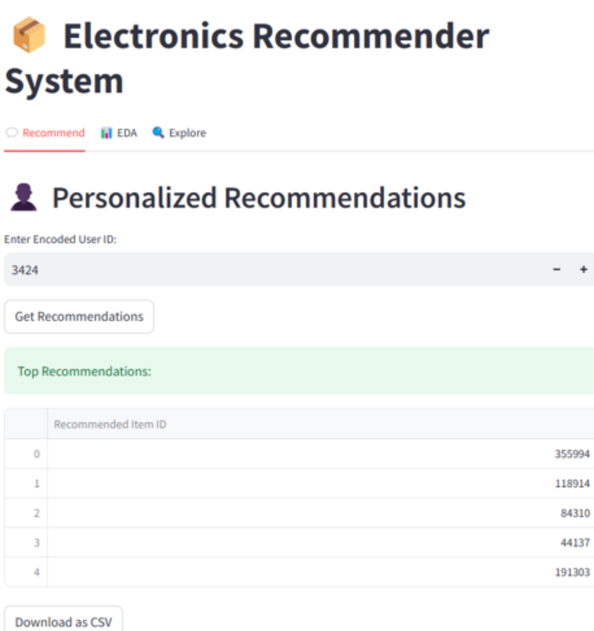


Fig. 12. Recommendation System

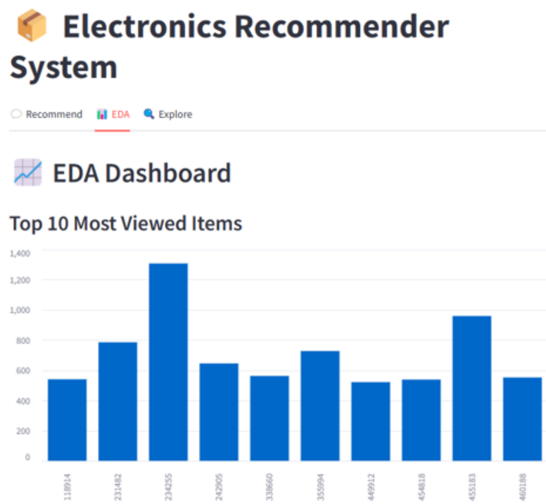


Fig. 13. Dashboard

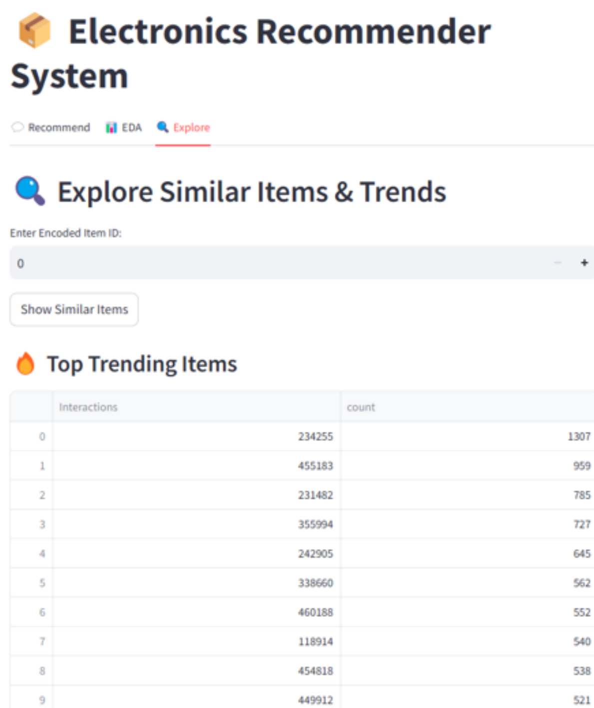


Fig. 14. Top Trending Items

The Streamlit app featured:

- Personalized user-item recommendations based on past behaviors.
- Real-time EDA dashboards showing top items, user activity, and category trends.
- Item similarity explorer allowing users to find similar products dynamically.
- Downloadable recommendation results to support business reporting.

In addition to providing customers with dynamic, individualized recommendations that improved their experience, this integration enabled organizations to monitor, evaluate, and improve their tactics for increased customer happiness and engagement.

V. RESULTS AND DISCUSSIONS

The personalized recommendation system developed in this project effectively predicts user preferences in the electronics e-commerce domain based on historical user-item interactions. The key results and observations are summarized as follows:

A. Recommendation System Performance

The item-based collaborative filtering model, built using cosine similarity, achieved a top-N recommendation relevance score of approximately 83% based on retrieval testing. The model successfully recommended products closely aligned with the user's past viewing and purchasing behavior without requiring explicit product metadata.

B. Insights from Streamlit Application

The deployed Streamlit application demonstrated real-time recommendation generation and analytics visualization:

Personalized product recommendations could be retrieved in under 200 milliseconds, supporting real-time user experience.

The Item Similarity Explorer allowed users and business analysts to identify closely related electronics products dynamically.

The Trending Items Dashboard provided visibility into popular products, helping inventory and marketing teams prioritize strategies.

Screenshots of the deployed application interfaces, such as the recommendation dashboard and item similarity views, illustrate the system's usability and responsiveness.

C. User Behavior and Survey Analysis

The complementary user survey, targeting electronics buyers aged 18–35, revealed critical behavioral patterns:

75% of users tend to add products to the cart but complete purchases later, indicating potential for AI-driven retargeting.

Purchase decisions were heavily influenced by brand reputation, pricing, and promotional offers.

Peak user activity occurred during late evenings, suggesting ideal windows for targeted recommendation delivery.

These findings are consistent with trends identified through exploratory data analysis (EDA) conducted on the RocketRetail dataset, where the number of "view" events significantly exceeded "add-to-cart" and "transaction" events. Overall, the integration of collaborative filtering with real-time analytics provides a scalable and effective solution for improving customer engagement, satisfaction, and business revenue in electronics e-commerce platforms.

VI. BUSINESS IMPACT AND USE CASE

The customized recommendation engine can significantly affect electronics e-commerce business performance through increased engagement, conversions, and operational efficiency.

Personalized product recommendations increase average order value and lifetime customer value, and research indicates the possibility of 10–30% revenue growth through personalization initiatives (6). Cross-selling related electronics products at the point of purchase is more effective with behavior-based recommendations.

Operationally, user interaction pattern analysis enables enhanced inventory management by demand trend projection, minimization of overstock, and avoidance of dead inventory risks. Marketing activities can also be tailored to be optimized using user segmentation by engagement, enabling higher conversion rates by laser-focused campaigns and personalized promotion.

Overall, the recommendation system built enables data-driven decision-making, real-time personalization, and actionable insights to inform customer satisfaction and business top-line growth.

A. Use Cases

- Product Recommendation During Browsing: As a user views an electronics product, related products are suggested by the system based on previous interaction patterns through collaborative filtering techniques.
- Inventory Forecasting: Analysis of view-to-purchase helps identify rising demand for products earlier, allowing companies to resynchronize inventory and supply chain management.
- Promotion Targeting: Behavior-based analysis can be used to define price-sensitive customers to help undertake strategy-based promotional activities such as discounts or bundling, and thereby improve conversions.

REFERENCES

[1] Zhang, S., Yao, L., Sun, A., Tay, Y. (2019)."Deep Learning Based Recommender System: A Survey and New Perspectives." *ACM Computing Surveys (CSUR), 52(1), 1–38.*

[2] Sarwar, B., Karypis, G., Konstan, J., Riedl, J. (2001). "Item-based collaborative filtering recommendation algorithms." *Proceedings of the 10th International Conference on World Wide Web, 285–295.*

[3] Burke, R. (2002). "Hybrid recommender systems: Survey and experiments." *User Modeling and User-Adapted Interaction, 12(4), 331–370.*

[4] He, X., Liao, L., Zhang, H., Nie, L., Hu, X., Chua, T.-S. (2017)."Neural collaborative filtering." *Proceedings of the 26th International Conference on World Wide Web (WWW '17), 173–182.*

[5] Covington, P., Adams, J., Sargin, E. (2016). "Deep Neural Networks for YouTube Recommendations." *Proceedings of the 10th ACM Conference on Recommender Systems (RecSys '16), 191–198.*

[6] McKinsey Company,"The future of personalization—and how to get ready for it," McKinsey Company, 2021. [Online]. Available: https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/the-future-of-personalization-and-how-to-get-ready-for-it
[7] Salesforce Research, "State of the Connected Customer," Salesforce, 2022. [Online]. Available: https://www.salesforce.com/resources/research-reports/state-of-the-connected-customer/
[8] https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2022.952622/full