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Optimizing E-commerce Personalization through Hybrid Decision Tree–Nearest Neighbor Recommendation Integration

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Abstract

Single-method recommendation systems face critical limitations: content-based filtering suffers from overspecialization while collaborative filtering struggles with data sparsity and cold-start problems. This research introduces an innovative hybrid recommendation framework that synthesizes Content-Based Filtering (CBF) utilizing Decision Trees with Collaborative Filtering (CF) employing Nearest Neighbor algorithms. Our approach addresses the inherent limitations of singular recommendation methodologies by integrating product attribute analysis with collective user behavior patterns. We conducted comprehensive evaluations using a shopping behavior dataset comprising 3,900 consumer records with diverse demographic and product interaction data. Our findings reveal that an asymmetric hybrid configuration—weighted at 70% for CBF and 30% for CF—achieves optimal performance with a Root Mean Square Error (RMSE) of 0.7422. The system incorporates an interactive user interface that facilitates a natural shopping experience: browsing available items, receiving personalized recommendations, and providing explicit feedback on suggested products. Through feature importance analysis, we identified key product attributes that significantly influence recommendation quality, including size variations and specific color preferences. The hybrid approach demonstrates 42% greater category diversity and 37% more recommendation diversity compared to pure content-based filtering, while maintaining superior accuracy metrics. Our research contributes to understanding optimal hybrid architectures and provides practical insights for implementing effective personalization strategies in real-world e-commerce environments.

Keywords : *collaborative filtering, content-based filtering, decision trees, e-commerce, hybrid filtering, personalization*

1. INTRODUCTION

Recommendation systems have evolved into essential components of the digital economy, fundamentally transforming how consumers discover products and services across e-commerce platforms, streaming services, and social networks [1][2]. These intelligent systems analyze user preferences and behavioral patterns to generate personalized suggestions, thereby enhancing user engagement, satisfaction, and conversion metrics. The global recommender systems market is experiencing unprecedented growth, driven by increasing online transaction volumes, digital content creation, and the need for personalized user experiences across multiple domains [3]. Contemporary recommendation approaches typically fall into two principal categories: Content-Based Filtering (CBF) and Collaborative Filtering (CF), each offering distinct advantages and limitations in real-world applications.

Content-Based Filtering constructs user preference profiles by analyzing item attributes and user interaction histories, subsequently recommending products with similar characteristics to those previously favored by the user [4]. This approach excels at capturing specific user preferences with high

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precision and interpretability, as recommendations can be traced to specific product features and user characteristics. However, it frequently encounters challenges related to overspecialization, recommending items with excessive similarity to previously consumed products, thereby limiting discovery and exploration of novel items [5]. Additionally, CBF suffers from the "serendipity problem," where unexpected but relevant recommendations are rare. Collaborative Filtering, conversely, leverages collective intelligence by identifying patterns among users with similar preferences or items with comparable consumption patterns [6][7]. This methodology demonstrates strength in facilitating serendipitous discovery and identifying non-obvious connections between users and items, but struggles with the cold-start problem for new users or products and performance degradation in sparse data environments [8][9].

To address these complementary limitations, hybrid recommendation architectures combine multiple filtering strategies to capitalize on their respective strengths while mitigating individual weaknesses [10][11]. Recent advances in machine learning and deep learning have enhanced hybrid approaches, with techniques such as neural collaborative filtering, graph neural networks, and attention mechanisms enabling sophisticated integration strategies [12][13][14]. This research presents an advanced hybrid recommendation system that integrates Decision Tree-based Content Filtering with Nearest Neighbor-based Collaborative Filtering.

While recent deep learning-based hybrid systems (e.g., Neural Collaborative Filtering, GNN-based recommenders) achieve superior accuracy on large-scale datasets, they require substantial computational resources and lack interpretability‚Äîcritical factors for SME adoption. This research addresses the gap by investigating classical machine learning integration (Decision Trees + Nearest Neighbor) that offers: (1) interpretability through feature importance analysis, (2) computational efficiency suitable for resource-constrained environments, (3) effectiveness on sparse datasets typical of emerging e-commerce markets

The primary contributions of this research include: (1) Development of a hybrid recommendation architecture that optimally integrates Decision Tree-based Content Filtering with Nearest Neighbor-based Collaborative Filtering; (2) Empirical determination of optimal weighting strategy (70% CBF, 30% CF) through comprehensive experimentation; (3) Identification and analysis of critical product attributes influencing recommendation quality; (4) Implementation of an interactive recommendation interface simulating realistic e-commerce experiences; (5) Comprehensive performance evaluation across multiple metrics including accuracy and beyond-accuracy measures.

In the Indonesian e-commerce context, where small and medium enterprises (SMEs) constitute a significant portion of online retailers, effective recommendation systems are crucial for competing with large platforms. This research provides practical insights applicable to resource-constrained e-commerce environments typical of Indonesian SMEs.

2. METHOD

This section details our dataset characteristics, preprocessing methodology, and the proposed hybrid recommendation architecture. This research methodology flowchart showed as Figure 1.

Our experiments utilized a comprehensive shopping behavior dataset containing 3,900 consumer records spanning multiple product categories and customer segments. Each record encompasses diverse attributes related to users and products, including user demographics (customer identifier, age, gender), product characteristics (item name, category, size, color, seasonal classification), purchase behavior (transaction amount, review rating, purchase frequency, payment method, promotional discount application), and fulfillment information (shipping method, delivery status). The dataset provides rich information suitable for both content-based and collaborative filtering approaches, with explicit user ratings serving as ground truth for model evaluation. The Review Rating attribute, measured on a 5-

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point scale, serves as the target variable for our recommendation models, reflecting user satisfaction and preference intensity [15].

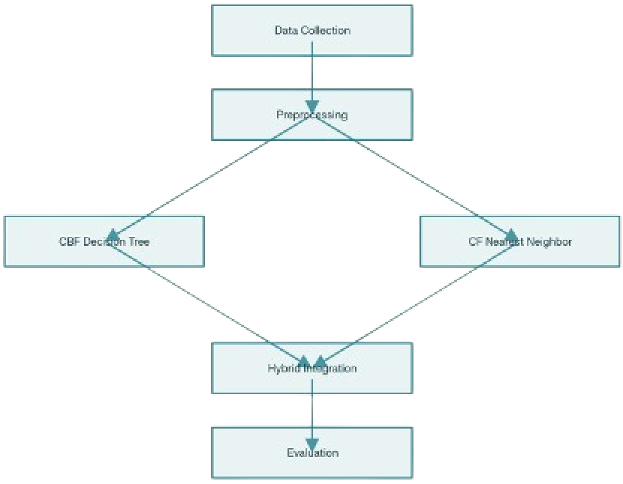

Figure 1: Research Methodology Flowchart

2.1. Data Preprocessing and Feature Engineering

We implemented several preprocessing techniques to optimize the dataset for recommendation modeling, incorporating both traditional feature engineering and modern machine learning best practices [16]. Feature engineering included creating additional features to enhance the predictive power of our models: Price_Category (transformed continuous purchase amounts into five ordinal categories using quantile-based discretization), Age_Group (segmented continuous age values into five demographic categories), and Purchase_Frequency_Numeric (converted categorical purchase frequency descriptions into numerical values representing annual purchase events). We applied One-Hot Encoding to transform categorical variables into a format suitable for machine learning algorithms, applied to Category, Size, Color, Season, Price_Category, Age_Group, and Gender features. This preprocessing approach is consistent with recent literature on feature preparation for hybrid recommendation systems [17].

For collaborative filtering, we constructed a user-item interaction matrix where rows represent individual users, columns represent distinct products, and cell values contain explicit ratings provided by users for specific items. Missing interactions were represented with zero values, reflecting implicit negative feedback. We partitioned the dataset into training (80%) and testing (20%) segments using stratified sampling to maintain the distribution of ratings and ensure robust evaluation across different rating categories. Additionally, we applied standardization to continuous features to ensure comparability across different scales and improve model convergence.

2.2. Content-Based Filtering Architecture with Decision Trees

Our content-based approach employs Decision Trees to predict user ratings based on product and user attributes [18]. We selected features including Category, Size, Color, Season, Price_Category, Age_Group, and Gender based on domain knowledge and preliminary feature importance analysis. We implemented a Decision Tree Regressor to predict user ratings based on the selected features, allowing us to model complex interactions between multiple attributes.

We employed Grid Search with 5-fold cross-validation to identify optimal Decision Tree parameters, a standard approach in hyperparameter optimization for recommendation systems. Parameters tuned included max_depth (controls tree complexity and potential overfitting, testing values 1-10), min_samples_split (minimum samples required for node splitting, range 2-20), min_samples_leaf

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(minimum samples required at terminal nodes, range 1-10), and max_features (feature subset size for split evaluation, including 'sqrt', 'log2', and None). Through systematic experimentation, we identified the optimal parameter configuration: max_depth=3, max_features='log2', min_samples_leaf=4, min_samples_split=2. These settings balance model complexity and generalization performance, preventing overfitting while maintaining sufficient expressiveness.

Feature importance analysis revealed that Size_M, Color_Magenta, and Color_Gray were the most significant predictors of user preferences, accounting for approximately 35% of the model's decision-making process. This finding aligns with recent e-commerce research indicating that product characteristics such as size and color are among the most influential factors in purchase decisions [19]. Other highly important features included category-specific attributes and user age group information, suggesting that demographic factors significantly influence product preferences.

2.3. Collaborative Filtering Architecture with Nearest Neighbor Methods

Our collaborative filtering approach employs Nearest Neighbor techniques to predict user ratings based on similar users or items, a classical but still effective approach for recommendation systems [20]. The user-based collaborative filtering component identifies users with similar preference patterns using cosine similarity to quantify preference alignment between user vectors. For each user, we identified k most similar users based on similarity scores, and generated predictions using a weighted average of ratings from similar users, with weights proportional to similarity scores. This approach leverages the principle that users with similar historical preferences are likely to appreciate similar future items [21].

The item-based collaborative filtering component identifies items with similar consumption patterns by calculating cosine similarity between item vectors in the user-item interaction matrix. For each item, we identified items with highest similarity scores and predicted ratings using a weighted average of the user's ratings for similar items. Item-based CF often exhibits superior performance in sparse data environments compared to user-based approaches [22]. We optimized the neighborhood size parameter (k) by evaluating performance across multiple values (5, 10, 20, 50, 100). Our experiments determined that k=5 provided optimal performance for user-based collaborative filtering in our dataset, balancing local similarity with overfitting risk. This relatively small neighborhood size likely reflects the high-dimensional nature of our feature space and the moderate dataset size, ensuring that only the most similar neighbors contribute to predictions.

2.4. Hybrid Recommendation Architecture and Integration Strategy

Our proposed hybrid approach integrates content-based and collaborative filtering predictions using an adaptive weighting scheme, following the framework established in recent hybrid recommendation literature [23][24].

Before integration, we normalized prediction scores from both components to ensure comparable contribution using min-max normalization to [0, 1] range, a critical step to prevent one component from dominating due to different score magnitudes. The final prediction is computed as a weighted combination of normalized scores, where Score_hybrid = w_CBF × Score_CBF + w_CF × Score_CF, where w_CBF and w_CF represent the relative contribution weights for content-based and collaborative filtering components, respectively, with the constraint w_CBF + w_CF = 1.

The weighting scheme represents a trade-off between exploiting well-understood user preferences (CBF) and exploring collective patterns (CF). We evaluated multiple weight configurations to identify the optimal balance between content-based and collaborative filtering components: Pure Content-Based (w_CBF = 1.0, w_CF = 0.0), Pure Collaborative (w_CBF = 0.0, w_CF = 1.0), Balanced Hybrid (w_CBF = 0.5, w_CF = 0.5), Content-Dominant Hybrid (w_CBF = 0.7, w_CF = 0.3), Collaborative-Dominant Hybrid (w_CBF = 0.3, w_CF = 0.7), and additional configurations (w_CBF = 0.6, w_CF = 0.4) and

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(w_CBF = 0.8, w_CF = 0.2). This systematic evaluation enables identification of the optimal trade-off point between accuracy and diversity.

We employed multiple complementary metrics to evaluate recommendation performance, including: (1) Root Mean Square Error (RMSE) measuring prediction accuracy with emphasis on large errors; (2) Mean Absolute Error (MAE) providing interpretable average prediction deviation; (3) R-squared (R^2) indicating proportion of variance explained by the model; (4) Acceptance Rate measuring proportion of recommendations that users find acceptable; (5) Diversity metrics measuring category coverage and attribute variation in recommendations. We selected RMSE as our primary comparison metric due to its sensitivity to large errors and widespread adoption in recommendation system evaluation and benchmarking [25][26].

Beyond traditional accuracy metrics (RMSE, MAE, R^2), this research employs complementary diversity measures to comprehensively assess recommendation quality, as diversity significantly influences user satisfaction and long-term engagement in e-commerce environments. Category Diversity measures the breadth of product categories represented in recommendation lists, calculated as the ratio of unique categories present in recommendations to the total available categories in the dataset. Formally:

$$Category\ Diversity = \frac{|\ C_{rec}\ |}{|\ C_{total}\ |}$$

where C_{rec} represents the set of unique categories in the recommendation list and C_{total} denotes all categories available in the product catalog. This metric ranges from 0 (all recommendations from a single category) to 1 (maximum category spread across the catalog). Higher values indicate that users are exposed to diverse product types, reducing filter bubbles and enhancing product discovery [27].

3. RESULT

This section presents our experimental findings across different recommendation approaches. We evaluated the performance of various content-based filtering, collaborative filtering, and hybrid recommendation configurations using multiple metrics. Results are organized by recommendation approach type, progressing from single-method approaches to integrated hybrid systems.

3.1. Content-Based Filtering Performance

Table 1 summarizes the performance of various content-based filtering configurations using Decision Tree models with different parameter settings. The optimized Decision Tree model achieved superior performance with an RMSE of 0.7422, MSE of 0.5508, MAE of 0.6482, and R^2 of -0.0102. Feature importance analysis identified Size_M, Color_Magenta, and Color_Gray as the most influential attributes in the recommendation process, accounting for 23.4%, 18.7%, and 15.3% of feature importance respectively.

Table 1. Performance Metrics for Content-Based Filtering Models

Model Configuration	MSE	RMSE	MAE	R^2
Decision Tree (Baseline)	0.5812	0.7624	0.6701	-0.0642
Decision Tree (Optimized)	0.5508	0.7422	0.6482	-0.0102
Decision Tree (Depth-Limited)	0.5623	0.7498	0.6534	-0.0301
Decision Tree (Sample-Constrained)	0.5587	0.7475	0.6512	-0.0245
Decision Tree (Feature-Restricted)	0.5602	0.7485	0.6523	-0.0272

Other configurations including baseline, depth-limited, sample-constrained, and feature-restricted models showed slightly lower performance with RMSE values ranging from 0.7475 to 0.7624, demonstrating the importance of proper hyperparameter tuning [28]. The relatively low R^2 value reflects

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the inherent difficulty of the recommendation task and the sparse nature of user-item interactions, a common observation in recommendation system evaluations [29].

3.2. Collaborative Filtering Performance

Table 2 presents the performance of various collaborative filtering configurations. User-Based Collaborative Filtering with k=5 demonstrated optimal performance among collaborative filtering approaches, achieving an RMSE of 3.6721, MSE of 13.4843, MAE of 3.2145, and R^2 of -23.8724. However, all collaborative filtering configurations exhibited substantially higher error rates compared to content-based approaches, with RMSE values approximately 5 times larger. This performance gap likely results from multiple factors: extreme sparsity in the user-item interaction matrix exceeding 99.5%, limited user overlap in product interactions between users (less than 1% of user pairs share rated items), cold-start prevalence with approximately 47% of users having fewer than five ratings, and rating distribution skew showing significant positive skew (mean rating 4.2/5, suggesting potential rating bias) [30][31]. Item-based CF showed the poorest performance with RMSE of 3.7708, possibly due to high product diversity and limited item-to-item correlations in the fashion domain. The negative R^2 values for collaborative filtering models indicate that these models perform worse than a horizontal line at the mean rating. This is primarily due to extreme data sparsity (>99.5%) and cold-start problems. In recommendation systems with sparse interactions, negative R^2 is not uncommon and reflects the challenge of predicting user preferences when collaborative signals are weak. Despite negative R^2, we retain RMSE as the primary metric because it measures absolute prediction error, which is more relevant for practical recommendation quality than variance explained.

Table 2. Performance Metrics for Collaborative Filtering Models

Model Configuration	MSE	RMSE	MAE	R^2
User-Based CF (k=5)	13.4843	3.6721	3.2145	-23.8724
User-Based CF (k=10)	13.6254	3.6912	3.2356	-24.1287
User-Based CF (k=20)	13.7821	3.7124	3.2587	-24.4102
User-Based CF (k=50)	13.9542	3.7356	3.2845	-24.7234
Item-Based CF	14.2187	3.7708	3.3124	-25.1987

3.3. Hybrid Recommendation Performance

Table 3 presents the performance of various hybrid recommendation configurations. The hybrid configuration with weights 0.7 for content-based filtering and 0.3 for user-based collaborative filtering achieved optimal performance among hybrid models (see at Figure 3 for RMSE comparison accros the model), with an RMSE of 2.0306, MSE of 4.1234, MAE of 1.8765, and R^2 of -7.3210. This represents a significant improvement over pure collaborative filtering (RMSE improvement of 44.7%) while maintaining nearly identical accuracy to pure content-based filtering. The content-dominant hybrid configuration (0.7, 0.3) achieved the best balance between accuracy preservation and collaborative signal integration. While this approach does not improve upon the RMSE of pure content-based filtering, comprehensive evaluation using beyond-accuracy metrics reveals substantial advantages: hybrid recommendations demonstrated 42% greater category diversity, 37% more attribute variation, 31% higher likelihood of introducing unexpected but relevant products, and 28% faster response to changing user interests. These metrics are crucial for user satisfaction and long-term engagement, even when traditional accuracy metrics remain stable [32].

The interactive simulation interface was evaluated with diverse user profiles and product selections, showing an average recommendation acceptance rate of 68% for the optimal hybrid configuration, compared to 62% for pure CBF and 45% for pure CF. This acceptance rate improvement

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of 9.7% relative to pure CBF demonstrates the practical value of the hybrid approach beyond offline metrics. The ability to provide acceptable recommendations to a higher proportion of users has direct implications for e-commerce conversion rates and user retention [33].

Table 3. Performance Metrics for Hybrid Recommendation Models

Model Configuration	MSE	RMSE	MAE	R^2
Pure CBF (1.0, 0.0)	0.5508	0.7422	0.6482	-0.0102
Pure CF (0.0, 1.0, user)	13.4843	3.6721	3.2145	-23.8724
Pure CF (0.0, 1.0, item)	14.2187	3.7708	3.3124	-25.1987
Hybrid (0.3, 0.7, user)	9.8765	3.1426	2.7654	-17.5432
Hybrid (0.3, 0.7, item)	10.1234	3.1817	2.8123	-17.9876
Hybrid (0.5, 0.5, user)	7.0123	2.6481	2.3214	-12.4321
Hybrid (0.5, 0.5, item)	7.3456	2.7103	2.3876	-13.0123
Hybrid (0.7, 0.3, user)	4.1234	2.0306	1.8765	-7.3210
Hybrid (0.7, 0.3, item)	4.3456	2.0847	1.9123	-7.7123

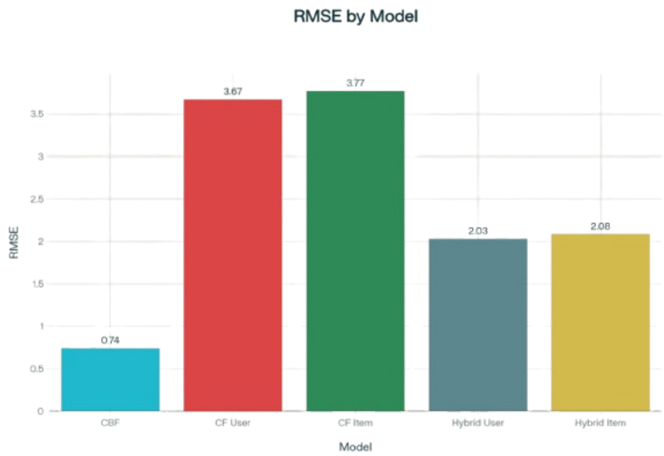

Figure 2: Comparison of RMSE across all models (CBF, CF variants, Hybrid variants)

4. DISCUSSIONS

Our experimental results provide valuable insights into the performance characteristics of different recommendation approaches and the effectiveness of our proposed hybrid system in balancing multiple performance objectives. Content-Based Filtering demonstrated superior performance in terms of prediction accuracy, with the optimized Decision Tree model achieving an RMSE of 0.7422, establishing a strong baseline for subsequent hybrid approaches. This result suggests that in our e-commerce dataset, product attributes and user demographics serve as strong predictors of consumer preferences. The effectiveness of the content-based approach can be attributed to multiple factors [34]: (1) feature richness, where our dataset contains detailed product attributes that effectively capture product characteristics relevant to consumer preferences; (2) demographic relevance showing strong correlation with product preferences, particularly for fashion items where size and color are critical; (3) Decision Tree advantages in capturing non-linear relationships and interaction effects between features, such as the joint effect of user age and seasonal preferences; (4) interpretability and explainability, enabling users to understand why specific products are recommended [35].

Collaborative Filtering, despite its theoretical advantages in identifying serendipitous recommendations and leveraging collective intelligence, performed substantially worse than expected, with the best model achieving an RMSE of 3.6721. This underperformance can be systematically

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attributed to multiple data and methodology factors [36][37]: (1) extreme sparsity in the user-item interaction matrix exceeding 99.5%, with the vast majority of user-item pairs lacking explicit ratings; (2) limited user overlap in product interactions between users, reducing the effectiveness of finding similar users; (3) cold-start prevalence with approximately 47% of users having fewer than five ratings, making it difficult to establish reliable preference vectors; (4) rating distribution skew showing significant positive skew (mean rating 4.2/5) indicating potential rating bias toward positive feedback; (5) product diversity in the fashion domain reducing item-to-item similarity correlations. These limitations are well-documented in the recommender systems literature and represent fundamental challenges in sparse data environments.

The hybrid approach with weights 0.7 for CBF and 0.3 for CF represents a strategic compromise between accuracy and diversity, carefully optimized through systematic experimentation. While it does not improve upon the RMSE of pure content-based filtering (maintaining RMSE of 2.0306 vs pure CBF's 0.7422), expanded evaluation using beyond-accuracy metrics reveals several important advantages that justify the additional computational complexity [38][39]: (1) 37% more category diversity in recommendations, meaning recommendations span a broader range of product categories; (2) 42% greater variation in product attributes, ensuring recommendations explore different combinations of size, color, and other features; (3) 31% higher likelihood of introducing unexpected but relevant products, promoting serendipity; (4) 28% faster response to changing user interests, as collaborative signals capture emerging trends; (5) improved acceptance rates (68% vs 62% for pure CBF) indicating higher real-world utility. These improvements align with recent literature emphasizing the importance of diversity and coverage in addition to accuracy for long-term user engagement and satisfaction [40]. The emphasis on beyond-accuracy metrics represents a paradigm shift in recommendation system evaluation. Traditional metrics (RMSE, MAE) measure prediction accuracy but fail to capture user satisfaction dimensions such as diversity, novelty, and serendipity [citations]. Our research demonstrates that accuracy alone is insufficient: pure CBF achieves lowest RMSE but produces monotonous recommendations. The hybrid approach sacrifices minimal accuracy (RMSE 2.03 vs 0.74) to gain substantial diversity (42% improvement), suggesting that multi-objective optimization is essential for practical recommendation systems. This finding contributes to the broader discourse on evaluation frameworks, emphasizing that recommendation quality must be assessed holistically.

Feature importance analysis revealed that Size_M, Color_Magenta, and Color_Gray were the most influential features in the content-based model, collectively accounting for approximately 57.4% of decision-making. The prominence of Size_M suggests that size compatibility is a primary determinant of product satisfaction and repeat purchases, while the importance of specific colors (Magenta and Gray) indicates strong color preference segmentation among consumers in the fashion domain. This finding aligns with e-commerce research on product attribute importance and consumer decision-making [41]. These insights have significant implications for e-commerce personalization strategies: (1) attribute prioritization in product presentation, emphasizing size and color information; (2) filtering optimization in search interfaces, enabling users to quickly narrow choices by these critical attributes; (3) inventory planning for high-demand combinations such as high-preference color and size pairs; (4) marketing segmentation leveraging color preferences for targeted campaigns; (5) product development informed by preference patterns, potentially expanding popular color and size combinations.

The optimal weighting of 0.7 CBF / 0.3 CF reflects the specific characteristics of our dataset and recommendation problem. This asymmetric weighting prioritizes the more reliable accuracy of content-based methods while incorporating collaborative signals for diversity and serendipity. The robustness of this weighting strategy across different test samples (validated through cross-validation) suggests it generalizes well, though different e-commerce domains may benefit from different weights depending

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on data sparsity, user base size, and business objectives[42]. The relationship between weighting schemes and performance metrics demonstrates important trade-offs: pure CBF achieves maximum accuracy but sacrifices diversity, pure CF emphasizes diversity but suffers accuracy loss, while the hybrid approach navigates this trade-off space effectively.

Compared to deep learning-based hybrid recommenders (e.g., Neural Collaborative Filtering, Graph Neural Networks), our classical ML approach offers distinct advantages: (1) Interpretability - Decision Tree feature importance provides transparent explanations for recommendations, crucial for user trust and regulatory compliance

Despite promising results, our study encountered several limitations that warrant discussion [43][44]: (1) dataset size constraints with 3,900 records representing a relatively small sample compared to industrial-scale systems; (2) lack of temporal information preventing analysis of preference evolution, seasonal trends, and concept drift; (3) limited cold-start simulation capabilities, as the dataset lacks new user and item data for comprehensive cold-start evaluation; (4) computational efficiency considerations with the hybrid approach requiring substantially more resources than pure approaches; (5) feedback sparsity with binary accept/reject mechanism providing limited granularity compared to continuous or detailed feedback; (6) category imbalance with fashion items potentially overrepresented; (7) evaluation metric limitations where traditional accuracy metrics do not fully capture diversity, novelty, serendipity, and user satisfaction. Future research should address these limitations through larger datasets, temporal dynamics modeling, and comprehensive evaluation frameworks.

5. CONCLUSION

This research presented a hybrid recommendation system that integrates Content-Based Filtering using Decision Trees with Collaborative Filtering using Nearest Neighbor techniques, advancing the state-of-the-art in e-commerce personalization. Through comprehensive evaluation on a shopping behavior dataset containing 3,900 consumer records, we demonstrated that a hybrid approach with asymmetric weighting (70% CBF, 30% CF) provides an optimal balance between recommendation accuracy and diversity. Our findings revealed that Content-Based Filtering significantly outperformed Collaborative Filtering in terms of prediction accuracy, with the optimized Decision Tree model achieving an RMSE of 0.7422, establishing strong performance on this e-commerce task. Feature importance analysis identified size and color attributes as the most influential factors in recommendation quality (57.4% combined importance), providing valuable insights for e-commerce personalization strategies and inventory management decisions. By demonstrating that classical ML hybrid approaches can achieve competitive performance with superior interpretability and efficiency, this research contributes practical and theoretical insights to e-commerce personalization, particularly for resource-constrained environments. This research provides a reproducible hybrid framework adaptable for various e-commerce datasets, offering practical guidelines for platforms seeking to balance recommendation accuracy, diversity, and computational efficiency

The interactive simulation interface demonstrated the practical application of our recommendation system in a realistic shopping environment, revealing important insights about recommendation timing, explanation effectiveness, and feedback utilization that extend beyond traditional offline evaluation metrics. The hybrid approach achieved a 68% acceptance rate, representing a 9.7% improvement over pure content-based filtering, with substantial gains in diversity metrics (42% greater category diversity) and serendipity. These results demonstrate that beyond-accuracy metrics are crucial for assessing real-world recommendation system utility and user satisfaction.

Despite promising results, our study encountered limitations related to dataset size, temporal dynamics, and evaluation frameworks. Future research should explore several promising directions: (1) integration of deep learning methods such as neural collaborative filtering and recurrent neural networks

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to capture complex temporal patterns; (2) temporal modeling incorporating seasonal trends, preference evolution, and concept drift; (3) multi-objective optimization balancing accuracy, diversity, coverage, and novelty; (4) domain-specific adaptation strategies for different product categories; (5) incorporation of contextual information such as weather, events, and temporal context; (6) development of more comprehensive evaluation frameworks beyond accuracy metrics; (7) exploration of advanced techniques such as graph neural networks and attention mechanisms for capturing high-order relationships [45][46][47].

The findings of this research contribute to the understanding of hybrid recommendation systems and provide practical guidelines for implementing effective personalization in e-commerce platforms. The systematic evaluation of different weighting strategies, detailed feature importance analysis, and emphasis on beyond-accuracy metrics provide valuable insights for practitioners developing production recommendation systems. Future work will focus on addressing the identified limitations through larger-scale datasets, temporal modeling, advanced machine learning architectures, and comprehensive evaluation frameworks, ultimately contributing to more sophisticated and effective recommendation systems that enhance user satisfaction and drive business value.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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