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Hybrid E-Recommendation System for Multi-Shop Environment[i]

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ABSTRACT

In the Kurdistan Regional Government, most computer shops and markets conduct their marketing offline and do not have electronic systems. Nevertheless, customers live in a digital age; they often face challenges in finding products among these markets and shops. The most common question that customers ask is which shop they should purchase from. Therefore, data from five laptop stores and ratings for markets were collected to build an integrated recommender system to help customers find products and select the best store. Our proposed system is a hybrid e-recommendation system that combines machine learning techniques to provide personalized shop and product recommendations. Methods include data collection from multiple laptop shops and dataset preparation. The system uses techniques such as hybrid/blended methods using singular value decomposition and K-nearest neighbors for collaborative filtering (CF) to recommend shops and products based on customer ratings, alongside term frequency-inverse document frequency vectorization and cosine similarity for content-based filtering. The CF's performance was evaluated using metrics like RMSE = 0.14 and MAE = 0.11, which demonstrated positive results for product and market recommendation. Overall, this study offers solutions through HE-RS to address key challenges such as market fragmentation, cold-start problems, and data scarcity.

Index Terms: Hybrid E-Recommendation System, Content-based Filtering, Collaborative Filtering, Machine Learning, E-Commerce

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1. INTRODUCTION

In the age of rapid digitalization, E-recommendation systems (E-RS) have emerged as indispensable tools in most fields, from e-commerce and entertainment to education, healthcare, and restaurants. These systems aim to reduce complexity by making relevant options easily available to users or by tailoring content to personal needs [1]. As consumer choice expands exponentially, the demand for efficient, accurate, and personal recommendation systems continues to grow.

Recommendation systems between people are often very effective for mutual assistance [2]. Therefore, it can be said that the idea originated from real-world human interactions. The recommender system appeared shortly after the World Wide Web was created, and both business and academics have investigated and used related technology extensively. One of the most popular online applications nowadays, recommender systems help billions of users every day by suggesting various types of material, such as news feeds, videos, e-commerce goods, music, movies, books, games, friends, jobs. These triumphant tales have demonstrated that recommender systems are capable of transforming large amounts of data into valuable information [3].

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Field has shifted from basic content-based filter (CBF) methods to advanced hybrid models that integrate CF, machine learning, and context-aware techniques. While CBF matches user preferences with item features, CF predicts preferences by analyzing the behavior of similar users. Despite their effectiveness, both methods face challenges such as cold-start issues and limited data, which can reduce their practical applicability.

The hybrid approach combining different filtering methods has been a significant step in overcoming these challenges. By combining insights from user behavior, product characteristics, and context, hybrid systems provide recommendations that are not only more accurate but also more diverse [4]. This is particularly helpful in regions, such as the Kurdistan Region, where fragmented markets make it difficult for consumers to find the products or services, they need across many different applications and systems.

Despite all efforts, the implementation of recommendation systems in fragmented markets is still understudied. Most present systems are designed for centralized e-commerce platforms with substantial user data, leaving a significant gap in these areas because markets operate independently and data are scarce and scattered. Addressing these gaps requires careful solutions and research that adapts to the unique challenges of fragmented ecosystems, enabling consumers to benefit from the personalized and detailed recommendations they expect in more developed markets.

2. E-RS

Recommender systems or E-RSs (sometimes rendered by terms such as platforms engines, algorithms, or software tools and techniques) are a subclass of data filtering systems that provide recommendations for items most relevant to a particular user. The aim of a recommender system is to create meaningful recommendations to a list of users for items or products that might interest them. These systems play an effective role in various areas, including e-commerce [5].

Typically, recommendations refer to various decision-making processes about what products to buy, what music to listen to, or what online news to read. RSs are used in many fields, with well-known examples taking the form of playlist generators for video and music services, product recommenders for online stores, content recommenders for social media platforms, open web content recommenders, or food recommendations in online restaurants. These systems can operate using a single type of input, such as music, or multiple inputs into and from across platforms, such as news, books, and search queries. There are also popular recommendation systems for specific topics, such as restaurants and online dating. Recommendation systems have also been developed to investigate research topics and experts, colleagues, and financial services [5].

2.1. Literature Review

Recommendation systems, as a field, have evolved rapidly, with several works addressing critical challenges, such as data sparsity, cold-start, and personalization, etc. These works are also closely related to this research, which employs a hybrid recommendation system (HRS) to improve poorly integrated and fragmented markets. In line with the overarching aim of our research, we reviewed some studies that offer insight and contribute to research goals.

Hasan and Ferdous (2024) highlight the effectiveness of HRSs that combine text-to-number transformation, matrix factorization techniques such as ALS, and cosine similarity for precise recommendations. Their study focuses on preprocessing, similarity calculations, and latent factor modeling, using the TMDB 5000 dataset and RMSE measures for evaluation. Their study further demonstrates how combining multiple methods in a hybrid approach improves the efficiency and accuracy of recommendations, especially in addressing data scarcity and enhancing system robustness [6].

Mouhiha *et al.* (2024) explore the combination of CF and CBF to address their individual limitations, such as the problem of cold start and data scarcity. Their study indicates that a HRS effectively improves accuracy and user satisfaction. Also, they describe various hybrid methods that tailor recommendations to user preferences by utilizing both user-item interactions and item specificity [7].

Loukili *et al.* (2023) investigate recommendation systems designed for e-commerce, using the FP-growth algorithm to analyze purchase patterns and generate personalized recommendations. Their study describes the decision-making challenges posed by the large number of product options. The rating metrics, including accuracy and conversions generated, also demonstrate how robust recommender systems have a direct impact on increasing sales and customer attraction, and highlight practical applications in real-world e-commerce platforms [8].

Cherkaoui *et al.* (2024) discusses using machine learning to predict customer behavior and improve strategies for marketing. This is achieved through the use of Apriori algorithms to mine the association rules and more sophisticated techniques, such as neural networks that are used to analyze user data to enhance understanding of the behavior of the users. Furthermore, their system concentrates on data segmentation, target estimation, and measures of effectiveness, thereby assisting businesses with realistic recommendations and improving the relevance of the goods recommended to users in highly competitive markets [9].

Ozturk *et al.* (2024) present a CrossGR model integrated with Graph Isomorphism Networks (GINs), facilitating the function of cross-market recommendation systems even with data sparsity and the limitations posed by the single markets. By employing GINConv layers and multi-layer perceptrons, the model derives insights into the typically complex user-item engagements, thus generating effective recommendations for different markets. Their novel concept in recommendation systems has demonstrated significant improvements in metrics, such as NDCG@10 and HR@10, suggesting the efficacy of graph-based learning approaches in recommendation systems [10].

The reviewed literature highlights various approaches, such as (hybrid recommendation models, machine learning approaches, graph-based methods, and NLP sentiment analysis). While these studies address issues such as data scarcity, personalization, and cold start issues, they do not specifically focus on fragmented market integration, a major challenge in many parts of the world, such as the Kurdistan Region.

This thesis aims to addressee the gap by combining different techniques such as CBF and CF, designed to enhance market recommendations in a complex multi-store environment. By collecting product information from multiple markets, the proposed system provides consumers with a unified shopping experience, overcoming the problems of fragmentation in the domestic e-commerce sector. Customers can also access multiple stores and products through a single application, which reduces customer search time and storage, especially on smartphones.

2.1.1. CBF

A content-based recommendation system [11] is a type of RS that functions based on the content and characteristics of items. For instance, each product has a set of attributes, and the system determines which attributes have contributed to the user satisfaction in the past.

2.1.2. Collaborative filter (CF)

CF is a powerful tool used to personalize web experiences based on other users' preferences and opinions. This method, known as CF, helps in examining large amounts of data by combining the perspectives of vast and interconnected online communities to make recommendations [12].

CF is divided into model-based and memory-based. Each has its own style and set of challenges. Memory-based systems use past evaluations to find users with similar tastes, while model-based systems use algorithms, such as genetic algorithms, to improve the accuracy of their recommendations.

CF applications: CF is widely used across various domains to provide personalized recommendations based on user preferences and behaviors, such as E-commerce, Music and Movie Recommendations, News, social media, etc.

2.1.3. HRS

HRSs combine multiple recommendation strategies to maximize their strengths. The choice of strategy depends on data characteristics. By effectively merging methods, HRSs deliver more accurate, adaptive, and user-personalized recommendations [4]. In another way, they are blended or mixed recommender systems.

Advantages of HRS over traditional RSs:

(i) Improved accuracy and personalization: By merging several recommendation algorithms, E-HRSs can provide recommendations that are more accurate and personalized based on the user's interests and preferences, surpassing the limitations of a single RS.

(ii) Scalable and flexible: HRS is more scalable than RS alone, as it can support more users and is also capable of being flexible by providing recommendations based on changes in customer behavior and application.

(iii) Enhanced robustness: As previously mentioned, the primary issues with a single RS that prevent it from making precise suggestions are data sparsity, biases, and inconsistencies. In contrast, HRS can operate well in this situation and more effectively handle modifications to user preferences, behavior, item attributes, and other elements.

(iv) Greater coverage: While single recommendation systems are constrained in their recommendation area and are only able to suggest certain goods, HRSs are able to go beyond these limitations and offer recommendations that are wider and more comprehensive.

Due to these benefits, researchers and businesses continue to refine HRSs, focusing on accuracy, algorithm combinations, and adaptability [4].

2.1.4. Machine learning

Machine learning (ML) is a subpart of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed [13]. ML has revolutionized the field of E-recommendation systems, making the systems more intelligent, more accurate in personal recommendations and enabling them to understand changes faster. E-commerce has expanded significantly due to its benefits, which has created a very good environment for the use of machine learning as a branch of AI. Due to the expansion of available information, there is a need for personalized experiences, addressing fraud detection and security challenges, enhancing supply chain optimization capabilities, and recognizing the importance of customer sentiment analysis [14]. Table I shows some ML models and algorithms that are used for E-RSs.

TABLE I: Machine learning models and algorithms used for E-RSs

Model/Algorithm	Description
K-means clustering	A popular unsupervised algorithm used to group similar users/items for recommendations.
Cosine similarity with K-NN	A similarity measure used in both content-based and collaborative filtering to compare vector closeness.
TF-IDF and cosine Similarity algorithms	The TF-IDF algorithm is used to evaluate the importance of words in a textual corpus. The cosine angle between two vectors is used by the cosine similarity method to calculate how similar they are.
Matrix factorization(MF)	Decomposes the user-item matrix into latent factors for collaborative filtering and hybrid systems.
Singular value decomposition (SVD)	A dimensionality reduction method used to improve the accuracy of collaborative filtering.
Latent Dirichlet Allocation (LDA)	A topic modeling technique used for literature or text-based content recommendation systems.
Convolutional neural networks (CNN)	Used to process structured data, such as images or sound for personalized music or movie recommendations.
Support vector machines (SVM)	A supervised learning algorithm used for classification in hybrid recommendation systems.
Gradient descent	Optimization method used in collaborative filtering to minimize error in rating prediction.
Reinforcement learning	Models' user interaction dynamically using contextual multi-armed bandit techniques for real-time recommendations.
Autoencoders	A neural network used in hybrid systems to reduce sparsity and integrate multiple recommendation approaches.
Bayesian networks	A probabilistic approach for predicting user preferences based on dependencies among variables.
Funk-SVD	A variation of SVD optimized for large-scale collaborative filtering by focusing on smaller matrices.
Decision trees	A supervised learning method used in collaborative filtering to classify user preferences.

3. METHODOLOGY AND SYSTEM ARCHITECTURE DESIGN

The system begins with data collection, followed by the design of a hybrid recommendation model aimed at producing effective results for the given problem. The methodology integrates two main approaches: CBF and CF.

3.1. Data Collection and Preparation

Figure 1 show the data collection and preparation process for five laptop shops and 1000 user ratings for shops and products. The *product datasets* include information about products from different shops. Each product dataset includes features such as (market name, brand name, processor type, processor brand, generations, RAM, storage capacity in GB, have SSD, HDD, graphics capacity, price, display size, display type, and color). The *User rating dataset* includes customer ratings. This allows the system to generate more accurate recommendations based on user preferences. It contains the user ID, shop ID, product ID, and the rating given by the consumer to the shops and products.

Figure 1 also illustrates the main preprocessing steps applied. Data preparation and preprocessing began by combining the datasets from five shops into a single dataset. Subsequently, data cleaning (such as removing duplicates, punctuation, and handling missing values), normalization (e.g., for price and rating), transformation (such as converting the rating matrix to a tabular format), and the selection of key features for building the e-recommendation system based on the features Kurdish users consider important when purchasing laptops were performed. In the final step, the rating dataset was divided into a training set (80%) and a testing set (20%) to evaluate model performance effectively.

3.2. Term Frequency-Inverse Document Frequency (TF-IDF) and Cosine Similarity

TF-IDF is a text analysis method used to calculate the relevance of words in a document when compared to a collection of documents. IDF reduces the weight of frequent words that exist in multiple documents, while TF measures

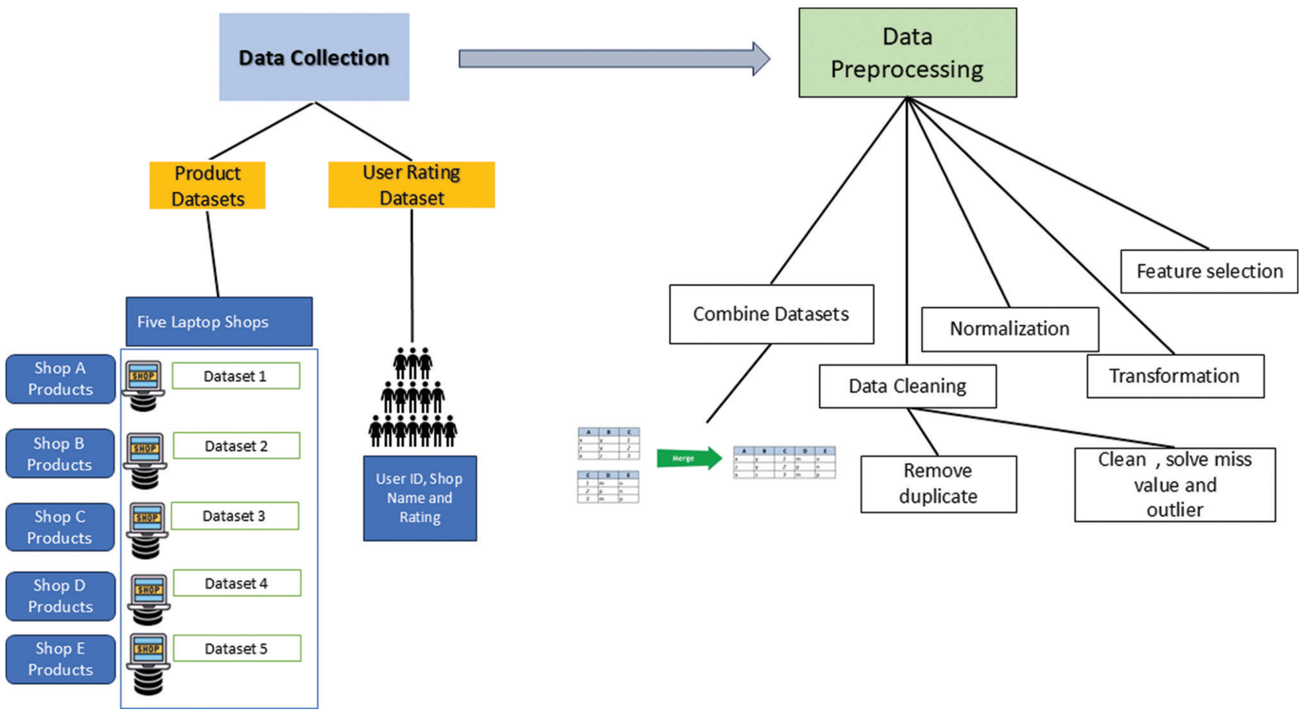

Fig. 1. Data collection and preparation process.

the frequency of a word's occurrence in a document. The TF-IDF equation is:

$$\text{TF-IDF} = \text{TF} \times \text{IDF}$$

Where is calculated as the number of times a word appears in a text or document divided by the total number of terms in that document, and IDF is computed as:

$$IDF = \log\left(\frac{N}{df}\right)$$

Where N is the total number of documents, and df is the number of documents containing that word. TF-IDF helps in filtering out less important words while highlighting meaningful ones in recommendation systems.

A measure called cosine similarity is used to evaluate how similar two text vectors are to each other as well as providing a quantitative measure of document similarity by calculating the cosine of the angle formed by two vectors in n-dimensional space. The formula is:

$$\cos(\theta) = \frac{A \cdot B}{|A||B|}$$

A and B are document vectors, and the numerator's dot product is divided by the product of their scales. Recommendation systems use both methods to detect product similarities based on descriptions in texts [15].

3.3. Singular Value Decomposition (SVD)

SVD is a matrix factorization algorithm that converts a matrix into three matrices for efficient representation and dimensionality reduction. This technique has found extensive applications across various areas, such as recommendation systems, where it has been shown to recommend new products and encourage repeat purchases, resulting in an improved user experience [16].

SVD in a recommendation system:
Input: A matrix where rows are users, columns are items (like movies), and the values are ratings.

SVD splits the matrix into three smaller matrices:
$A = U \cdot S \cdot V^T$
U: Describes the users.
S: Contains the importance of features.
V_T: Describes the items.

Using this, we can predict missing values in the original matrix, such as movies a user hasn't rated yet.

3.4. K-Nearest Neighbors (K-NN)

K-NN is an instance-based learning algorithm that is widely used in classification and regression problems [17]. Because it is so easy and supports large-dimensional data, it is widely used for text classification, image recognition, and medical diagnosis. Although algorithm performance may depend significantly on the distance used, it has been shown to achieve competitive results in most real-world applications. K-NN for recommendation system is a neat application, in which you can detect similar users or objects from their characteristics and propose them recommendations.

3.5. CBF Process

We combined multiple product attributes (such as price, brand, RAM, screen size, etc.) into a single row for each product. This row represents a general description of the product.

1. The TF-IDF Vectorizer is used to convert these combined product features into numerical vectors. This conversion transforms the textual information into a format suitable for similarity calculations. As the process is shown in Figure 2.
2. After converting product attributes and search queries into TF-IDF vectors, cosine similarity was used to compute and find the products that are most similar to the user's search query.
3. After generating initial recommendations, the results are filtered based on user-supplied parameters, such as RAM, screen size, and storage. Finally, the shops and products were sorted by their ratings and similarity score. Furthermore, Figure 2 illustrates the integration of TF-IDF and Cosine Similarity.

3.6. CF Process

The user ratings are normalized using normalization techniques to ensure all ratings are within the range of 0 to 1. This process reduces bias arising from different rating scales across users.

1. SVD is employed to analyze a sparse user-item evaluation matrix into latent factors representing user and market preferences. It enables the prediction of missing assessments by capturing underlying patterns in the data.
2. K-NN is also utilized to identify users or similar shops based on their evaluation patterns. This method offers interpretability by highlighting neighbors.
3. We combined SVD and K-NN to form a hybrid model. The SVD and K-NN predictions were weighted (40% SVD, 60% K-NN) to generate the final recommendation. This approach exploits the strengths of both algorithms to reduce errors and improve the accuracy of recommendations. Figure 3 illustrates the process flow of the CF approach, which integrates SVD with K-NN.

3.7. The Flowchart of the Proposed System

In Figure 4, the flowchart shows the user workflow in the E-RS. To begin with, the user can either create an account by

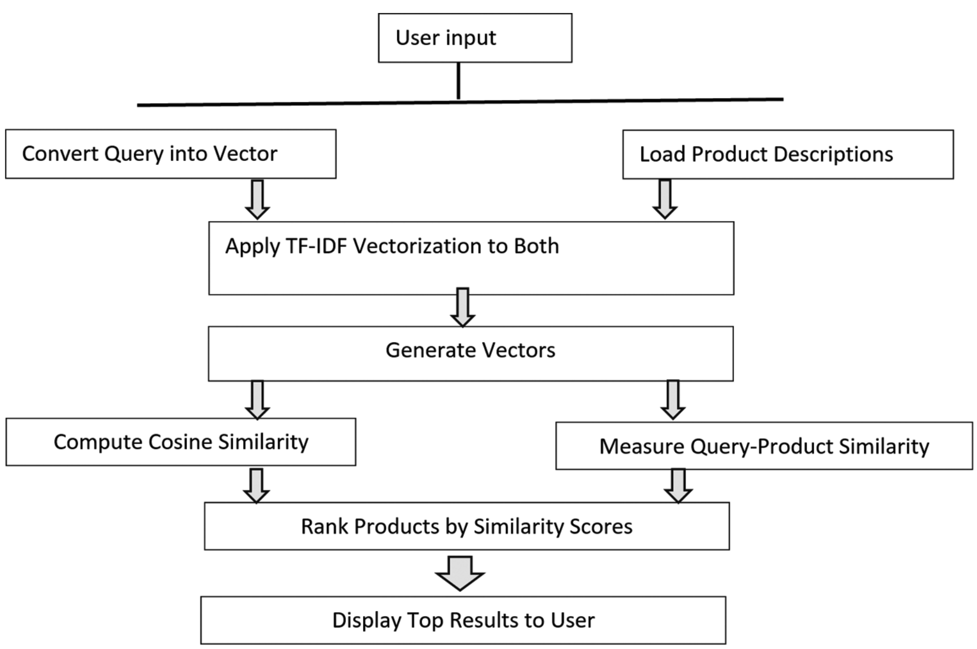

Fig. 2. Content-based filtering process.

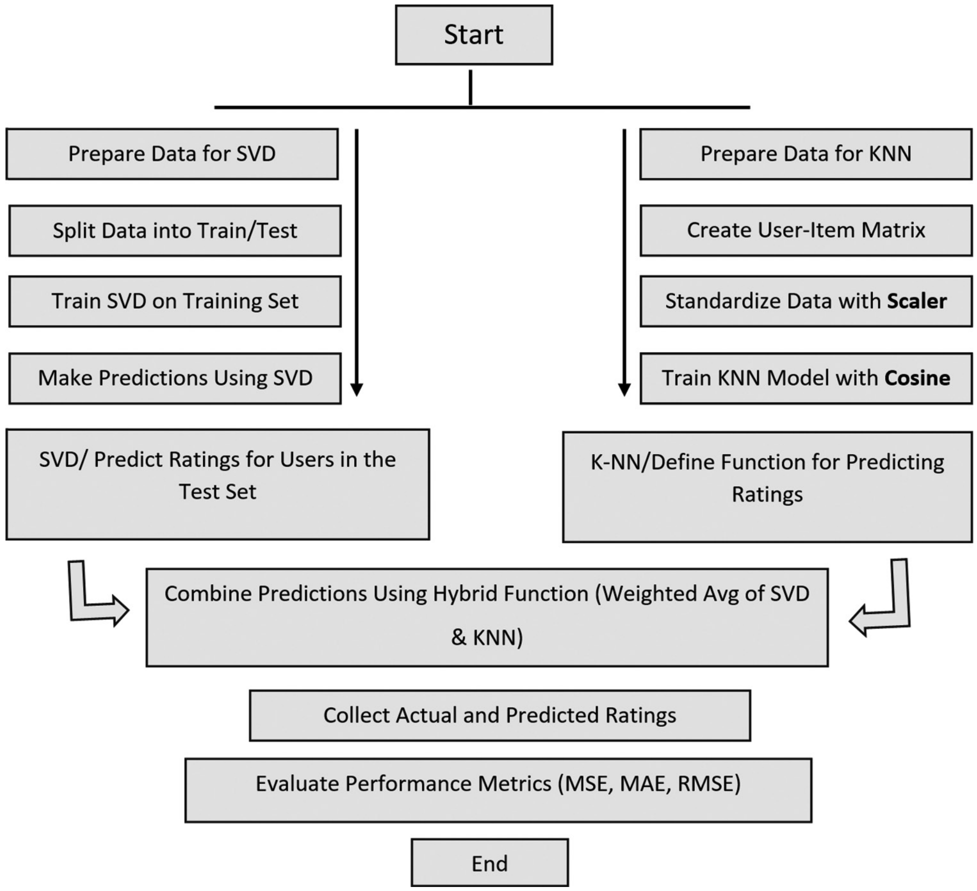

Fig. 3. Collaborative filter process.

registering or log in to their present account. Alternatively, they can search the system anonymously, limiting the level of personalization. Once a user is engaged, they can start browsing products. The system uses a combination of recommendation techniques. For example, if a user searches for "RAM 32GB", the system uses CBF to analyze user search queries and compares them with product descriptions using techniques such as TF-IDF and cosine similarity, which helps the user to find laptops in multiple shops with similar attributes such as RAM, storage, and price. The user search result is ordered based on similarity score. For example, if shop A has a high similarity score, it will be shown at the top for the user. The system also makes use of CF for registered users to analyze past user behavior, such as ratings and compares it to the behavior of other users with similar interests. Algorithms, such as K-NN and SVD are used to detect these similarities and predict the shop and products that the consumer might like.

Finally, the hybrid recommendation system combines the strengths of both CBF and CF. This approach offers a more nuanced and accurate set of recommendations by taking into account both product characteristics and user ratings.

4. RESULTS AND DISCUSSION

```
# TF-IDF Vectorizer to convert text to numerical vectors
tfidf = TfidfVectorizer(stop_words='english')

# Fit and transform the combined features for all products
tfidf_matrix = tfidf.fit_transform(products_df['combined_features'])

# Transform the search query into the same TF-IDF space
query_tfidf = tfidf.transform([search_query])

# Compute cosine similarity between the search query and all products
cosine_sim = cosine_similarity(query_tfidf, tfidf_matrix)
```

4.1. CBF Implementation and Result

Figure 5 illustrates the top five recommended Apple products retrieved using CBF. The system computed the similarity scores using TF-IDF and cosine similarity. Higher scores indicate stronger textual similarity to the user's search. This figure shows that the most relevant match (0.773) is from the

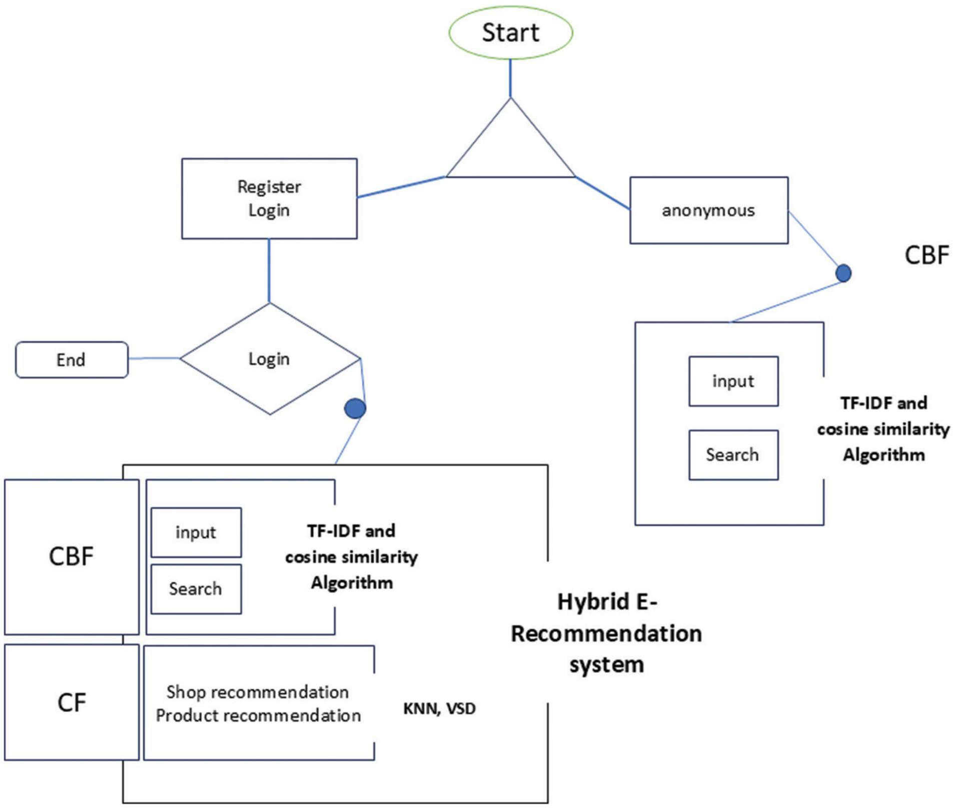

Fig. 4. Flowchart of the proposed system.

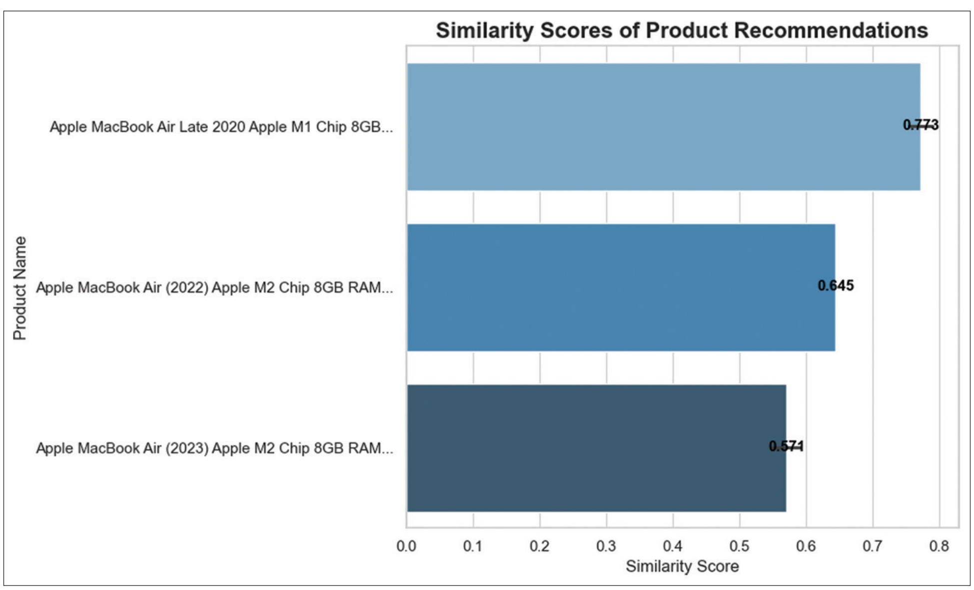

Fig. 5. Content-based filter similarity score result.

"Shop W" market, while other competitive options appear in "Shop R" and "Shop M_A".

The brief code sample in the screenshot above presents a fundamental CBF code structure. The CBF component relied on TF-IDF to convert textual product descriptions into numerical vectors that were then used to calculate cosine similarity. Cosine similarity measures the angle between two vectors in multidimensional space which provides a measure to find the similarity between user search and product attributes. These detailed calculations ensure that the best ranking related to user search is provided.

To evaluate the CBF approach in a real-world user-facing system, we consider an example of a user search with loosely defined features ("8 GB RAM core i5 gen 11 white hp"). As observed, this query exhibits characteristics of a user search with loosely defined features. The search results for this query were available from five distinct vendors. Figure 6 presents the results from a selection of these shops.

4.2. CF Implementation and Result

The model needs to be trained and tested after it is built. The dataset was partitioned into a testing set (20%) and a training set (80%). For evaluating the models, metrics, such as root mean squared error (RMSE), mean absolute error (MAE), and mean squared error (MSE) were used. The below screenshot for the sample code shows how SVD and K-NN are combined to improve shop and product recommendations.

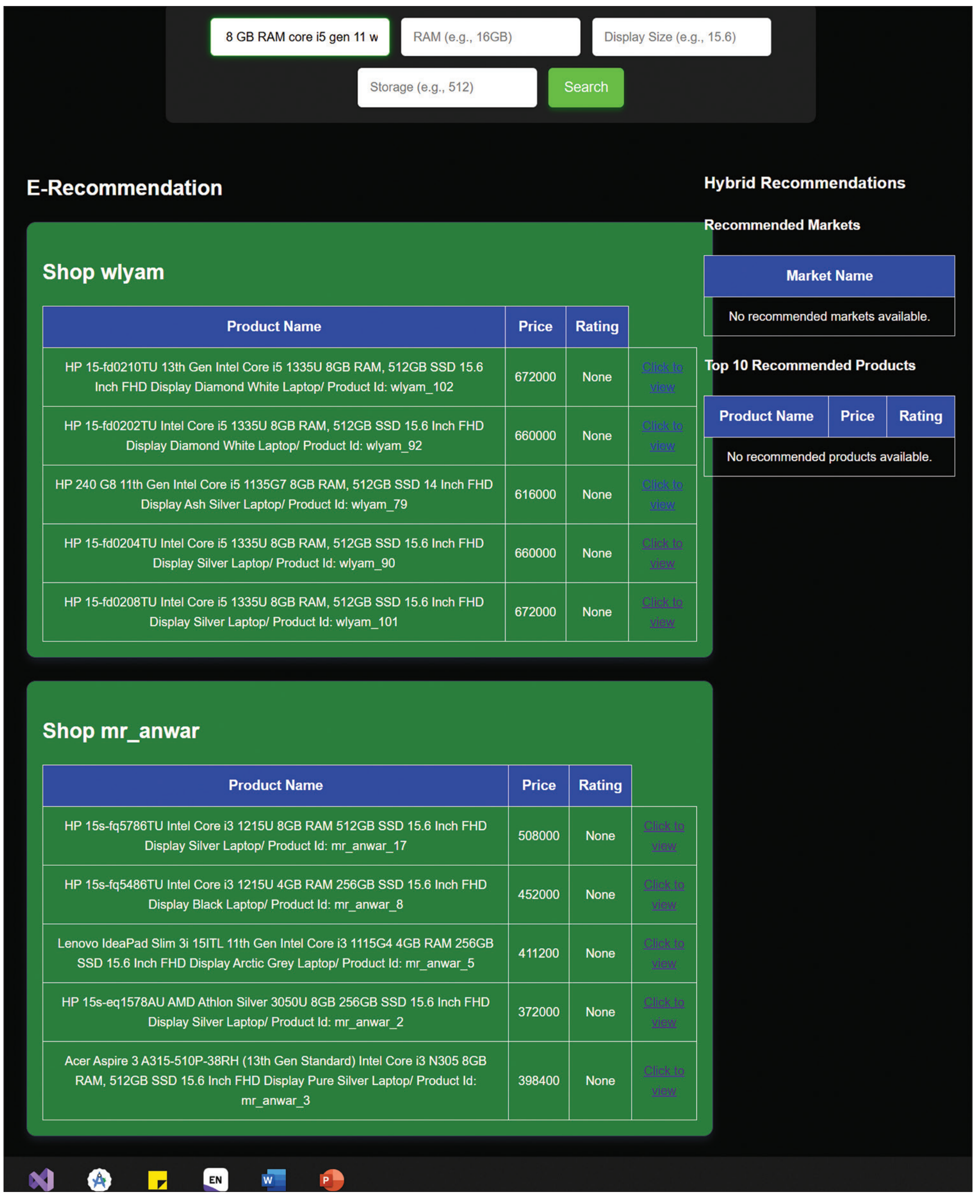

Fig. 6. User search example and content-based filter result.

```
#CF Result combination
# Combine predictions from KNN and SVD
def hybrid_predict(user, market):
    # Get SVD and KNN predictions
    svd_rating = svd_predicted_ratings.get(f"{user}-{market}", 0)
    knn_rating = knn_predict(user, market)

    # Weighted average of the two predictions
    return 0.4 * svd_rating + 0.6 * knn_rating
```

In addition to these results in table 2, the response time was also tested to evaluate the real-time performance of the hybrid proposal model. The test yielded an average prediction response time of 0.0020 s, or 2 ms, demonstrating the system's efficient and near-instantaneous shop recommendation capability. This outcome suggests that the model is effectively optimized for real-time applications, enabling it to handle user demands with minimal latency.

4.3. Hybrid E-Recommendation System Result

By bringing together both CBF and CF into one system, we create a hybrid recommendation model that takes the best of both worlds while reducing each method's weaknesses. The HE-RS model combines the feature-based approach from CBF, which uses product attributes to find similarities, and the behavior-based insights from CF, which look at user ratings and patterns to offer more personalized and robust recommendations. This means that even if a user hasn't rated many shops and products, CBF can still suggest items based on product features, while CF can step in when product details alone aren't enough to capture user preferences. Contextual and behavioral data are both included in the final recommendation outcome, which produces a system that can effectively handle problems, such as data lacking, new users, and modifying preferences. Furthermore, this hybrid approach not only improves the accuracy of recommendations but also creates a more intuitive and user-friendly shopping experience by continuously matching product recommendations and shop recommendations to changing consumer preferences. In Figure 7, what is on the right side of the system is the result of a customer's recommendation based on the rating they gave, in which machine learning algorithms play a role. The list on the left shows the results of the customer's search and the results according to the similarity of the user's search and products. In all stores, products are recommended by the recommender system based on CBF.

4.4. Discussion

Table 2 is shows the hybrid model (SVD with K-NN) gives better recommendations than the SVD model alone. Hybrid model has a lower RMSE (0.1435) and MAE (0.1147) compared to the SVD model, indicating that the hybrid approach makes more accurate predictions. SVD finds hidden patterns in the data, while K-NN improves prediction by comparing similar users. Thus, combining both methods can reduce errors and give better recommendations. The results of this study are presented in two ways that reflect real-world applicability. One of the important aspects that distinguishes this research from other studies is the development of a comprehensive system that integrates multiple recommendation techniques to enhance performance. The evaluation and results suggest that the prototype system is suitable for further development and optimization, and that a centralized recommendation platform can serve as a practical solution for mitigating challenges in fragmented markets. Instead of requiring each shop to develop its own application, which causes data dispersion, businesses can simply create an account within a unified system tailored to their specific industry, improving accessibility and user experience.

4.5. Comparative Analysis

To validate the performance of our hybrid recommendation system, we compare it with recent models that also apply hybrid or advanced recommendation techniques. As shown in Table III, our system combines SVD and K-NN for CF with TF-IDF and Cosine Similarity for CBF. The CF achieves a low RMSE of 0.14 and MAE of 0.11 on a sparse, custom laptop dataset. Furthermore, the CBF achieves successful performance in responding to customer searches. Compared to other studies, our system demonstrates higher precision and adaptability in market-specific recommendations.

TABLE II: Cross-validation result

Model	Metric	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean	Standard
SVD	RMSE	0.3185	0.3123	0.3184	0.3192	0.3179	0.3172	0.0025
	MAE	0.2713	0.2637	0.2741	0.2767	0.2688	0.2709	0.0045
Hybrid (SVD+K-NN)	RMSE	—	—	—	—	—	0.1435	—
	MAE	—	—	—	—	—	0.1147	—

RMSE: Root mean squared error, MAE: Mean absolute error, SVD: Singular value decomposition, K-NN: K-nearest neighbor

Fig. 7. Hybrid e-recommendation screen result.

TABLE III: Comparison of HE-RS with other studies

Studies	RMSE	MAE	Dataset	CF method	CBF method	Key insights
HE-RS	0.14	0.11	Laptop market (Custom, Sparse)	SVD, K-NN	TF-IDF, Cosine similarity	Accurate hybrid recommendations tailored to sparse, real-world e-commerce
Hasan and Ferdous [6]	0.8951	–	TMDB 5000	ALS	Cosine similarity	Hybrid approach; improved accuracy compared to basic CF
Mouhiha *et al*. [7]	0.22 (RMS Prop), 0.14 (SGD)	–	Movie lens	–	Deep features, cosine	Deep learning improved hit rate (0.89), NDCG@10=0.64
Ozturk *et al*. [10]	–	–	Cross-market dataset	Graph isomorphism networks	–	Best NDCG@10=0.6524, HR@10=0.7609 in cross-market scenario

HE-RS: Hybrid electronic recommendation system, RMSE: Root mean squared error, MAE: Mean absolute error, SVD: Singular value decomposition, K-NN: K-nearest neighbor, CBF: Content-based filter, CF: Collaborative filtering

5. CONCLUSION

In this study, we have designed a hybrid electronic recommendation system (HE-RS) for a multi-shop environment, such as the Iraq-Kurdistan region, to address market fragmentation. We have combined methods within the system, such as CBF and CF. The system allows users to find shops and products based on shop ratings and product characteristics. The results indicate that the system can simplify customer search, and algorithms such as TF-IDF and cosine similarity were able to produce accurate results for customer queries across multiple shops. The system also improved the quality of recommendations by using advanced machine learning techniques, such as the combination of SVD and K-NN algorithms to analyzing customer reviews, which effectively predicted customer preferences and achieved high performance. Moreover, the system was able to address challenges such as the cold start problem, limited data, and diverse user preferences. A major solution to using multiple applications for various shops is provided by this system. Stores can register on a centralized platform, which allows customers to browse for items in many marketplaces using a single interface; this reduces the customer search time.

5.1. Future Work

a. Integrate real-time user feedback.
b. Use deep learning techniques to improve recommendation accuracy.
c. Analyze more user behavior, such as clicks or browsing history.
d. Integrate the system with mobile applications.

Finally, our research demonstrates that a HE-RS offers a means to address market fragmentation, provides effective recommendations for customers, and generates increased opportunities for businesses.

REFERENCES

[1] F. Ricci, L. Rokach and B. Shapira. Recommender Systems: Techniques, Applications, and Challenges. In: "*Recommender Systems Handbook*". Springer Science and Business Media, Germany, pp. 1-35, 2021.

[2] S. Moica, C. Veres Harea and L. Marian. "*Effects of Suggestion System on Continuous Improvement: A Case Study*". IEEE, United States, pp. 592-596, 2018.

[3] Z. Dong, Z. Wang, J. Xu, R. Tang and J. Wen. "*A Brief History of Recommender Systems*". [arXiv Preprint], 2022.

[4] K. Bodduluri, F. Palma, A. Kurti, I. Jusufi and H. Löwenadler. "Exploring the landscape of hybrid recommendation systems in E-commerce: A systematic literature review". *IEEE Access*, vol. 12, pp. 28273-28296, 2024.

[5] F. Ricci, L. Rokach and B. Shapira, editors. Recommender Systems: Techniques, Applications, and Challenges. In: "*Recommender Systems Handbook*". New York, Springer US, pp. 1-35, 2022.

[6] M. R. Hasan and J. Ferdous. "Dominance of AI and machine learning techniques in hybrid movie recommendation system applying text-to-number conversion and cosine similarity approaches". *Journal of Computer Science and Technology Studies*, vol. 6, no. 1, pp. 94-102, 2024.

[7] M. Mouhiha, O. A. Oualhaj and A. Mabrouk. "*Combining Collaborative Filtering and Content Based Filtering for Recommendation Systems*". IEEE, United States, pp. 1-6, 2024.

[8] M. Loukili, F. Messaoudi and M. El Ghazi. "Machine learning based recommender system for e-commerce". *IAES International Journal of Artificial Intelligence*, vol. 12, no. 4, pp. 1803-1811, 2023.

[9] N. Cherkaoui, K. El Handri, M. D. Y. Tanoga, Y. El Hassani and A. Errafyg. "Consumer behaviour: Analysing marketing campaigns through recommender systems and statistical techniques". *Marketing and Management of Innovations*, vol. 15, no. 3, pp. 1-12, 2024.

[10] S. Ozturk, A. B. Ercan, R. Tugay and Ş. G. Öğüdücü. Enhancing Cross-Market Recommendation System with Graph Isomorphism Networks: A Novel Approach to Personalized User Experience. In: "*Proceedings of the 2024 9th International Conference on Machine Learning Technologies*", 2024.

[11] D. Patel, F. Patel and U. Chauhan. "Recommendation systems: Types, applications, and challenges". *International Journal of Computing and Digital Systems*, vol. 13, pp. 2210-2142, 2023.

[12] J. B. Schafer, D. Frankowski, J. Herlocker and S. Sen. Collaborative filtering recommender systems. In: P. Brusilovsky, A. Kobsa and W. Nejdl, editors. "*The Adaptive Web: Methods and Strategies of Web Personalization*". Springer, Berlin, Heidelberg, pp. 291-324, 2007.

[13] T. M. Mitchell. "*Machine Learning*". Vol. 1. McGraw-Hill, New York, 1997. Available from: https://www.pachecoj.com/courses/csc380_fall21/lectures/mlintro.pdf [Last accessed on 2025 Apr 19].

[14] F. Weiner, P. L. Teh, and C. B. Cheng. "*Systematic Review of Machine Learning in Recommendation Systems Over the Last Decade*". Springer Nature Switzerland, Cham, 2024.

[15] M. Chiny, M. Chihab, O. Bencharef and C. Younes. "*Netflix Recommendation System Based on TF-IDF and Cosine Similarity Algorithms*". no. BML, pp. 15-20, 2022. Available from: https://www.scitepress.org/Link.aspx?doi=10.5220/0010727500003101 [Last accessed on 2025 Apr 19].

[16] B. Sarwar, G. Karypis, J. A. Konstan and J. T. Riedl. Application of dimensionality reduction in recommender system-a case study. In: "*ACM WebKDD 2000 Web Mining for E-Commerce Workshop*". Boston, MA, USA, 2000.

[17] O. Kramer. K-Nearest Neighbors. In: "*Dimensionality Reduction with Unsupervised Nearest Neighbors*". Springer, Berlin, Heidelberg, 2013, pp. 13-23.