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Personalized Savings Product Recommendations Using a Hybrid Approach

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Abstract

Financial sources are crucial for the stable business success of financial institutions, and banks actively offer savings products to customers to enhance their sources. Therefore, attracting customers by providing the right products that align with their preferences is essential. A recommendation system helps customers select suitable products and has demonstrated business value through increased sales and institutional income. While recommendation systems have found success in areas like e-commerce and entertainment, implementing them in the financial sector remains challenging due to a lack of explicit customer feedback such as ratings and reviews. This study addresses this gap by developing a hybrid recommendation system specifically for a bank's savings products. By utilizing transaction-based implicit feedback and combining content-based filtering with collaborative filtering, we have designed a model tailored for the banking context. We used real banking data from Mongolia covering the period 2021–2023. Among individual models, the content-based method showed the highest accuracy. The hybrid model outperformed both content-based and collaborative filtering approaches when the content weight $\alpha = 0.85$, achieving the lowest RMSE of 1.260 and MAE of 0.980. This result demonstrates the effectiveness of a well-balanced hybrid approach in predicting customer preferences in banking savings products. This research contributes to bridging the gap between recommendation technologies and the financial domain, providing practical implications for personalized financial product offerings where traditional feedback is absent.

Keywords: recommendation system, savings products, machine learning, collaborative filtering, content-based filtering, hybrid approach

1. Introduction

One of the vital objectives of financial institutions is to increase their financial resources, for that purpose, banks have been striving to sell their savings products to customers. If financial institutions can recommend appropriate savings products that match customers' preferences, it leads to increased sales and the financial institution's income by assisting customers in choosing their preferred products. The recommendation system is an intelligent application designed to assist the user to choose items or products (Jannach, 2019). Recommendation systems provide personalized recommendations to customers by analyzing customer data related to their preferences, behavior, and ratings (Temitope, 2020).

Implementing a recommendation system offers benefits for both customers and financial institutions. It helps customers to choose the right financial products by presenting alternative options tailored to their needs. Since the adoption of recommender systems in business is to increase product sales, for financial institutions, it increases the sales of a variety of deposit products and stable funding which can improve the ability to manage solvency and liquidity with less risk (Aggarwal, 2016).

Recommendation systems can be built using different approaches, including collaborative filtering, content-based methods, and hybrid techniques. A widely used approach is collaborative filtering, also referred to as a community-based approach, which utilizes both the preferences and behaviors of similar users along with those of the target user (Sharaf, 2022; Javed, 2021). Another approach is content-based filtering, which focuses on the attributes and characteristics of items or products (Pazzani, 2007). Lastly, hybrid methods combine collaborative filtering and content-based techniques to improve recommendation accuracy (Sharaf, 2022; Oyebode, 2020)

Although, numerous studies have explored recommender systems and their algorithms across various domains, such as e-commerce and entertainment (Shambour, 2022; Jena, 2022; Sharaf, 2022). However, there is limited research on adapting these systems to banking products and services. In e-commerce and other domains, user preferences are often explicitly gathered through item ratings or simple like/dislike interactions where users provide direct feedback on their experiences. In contrast, implicit ratings are not explicitly provided by users but can be inferred from user interactions or behavioral data, such as purchases, clicks, and transaction data. Unlike e-commerce platforms, banks typically do not require customers to rate their financial products, making it difficult to apply traditional recommendation techniques. One of the challenges in recommender systems is the absence of direct user feedback, such as product reviews and ratings, which are readily available in other domains (Klioutchnikov, 2020; Oyebode, 2020; Sharaf, 2022). Another key limitation is identifying suitable recommendations for new or prospective customers who have not yet interacted with banking products. This issue, commonly known as the cold-start problem, makes it challenging to provide personalized recommendations in the absence of prior user data (Aggarwal, 2016).

Several studies have explored recommender systems in the financial sector using different methodologies. Nair and Muralidharan (2020) compared multiple machine learning techniques

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applied to financial data, while Temitope et al (2020) introduced a graph-based recommender system for financial products. Wu and Li (2025) conducted a systematic literature review, distinguishing financial product recommendations from those in other domains. Barreau and Carlier (2021) developed a collaborative filtering algorithm incorporating temporal dynamics to provide adaptive financial recommendations. Oyebode and Orji (2020) proposed a hybrid recommender system combining item-based collaborative filtering with demographic data, while Klioutchnikov et al. (2020) designed a recommendation system specifically for financial intermediaries, aimed at filtering financial information and supporting decision-making. Other research has focused on customer retention and decision-making support. Gorgoglione and Panniello (2011) implemented a recommendation-based model to predict customer churn and suggest personalized retention strategies based on the behaviors of loyal customers.

The primary objective of this study is to identify the most suitable recommendation method for predicting user ratings of banking savings products. Banks offer a wide range of financial products, including savings accounts, checking accounts, investment products, and loans, each with distinct purposes and characteristics. As a result, the effectiveness of different recommendation techniques may vary based on the specific attributes of each product. Unlike typical consumer goods, savings products are investment-oriented and have unique features that influence user selection. The selection factors are influenced by product-specific attributes such as interest rates and product terms etc., (Jumena, 2022). While previous studies have focused on general financial product recommendations, this research is specifically designed for savings product recommendations in banking, considering their unique features. We implemented a hybrid approach that combines content-based filtering and collaborative filtering, optimizing weight parameters to enhance prediction accuracy.

For this research, we used historical data on savings product usage from a well-established bank in Mongolia, covering the period from 2021 to 2023. The findings indicate that, for savings products, the content-based recommendation approach outperforms collaborative filtering in terms of prediction accuracy. Moreover, a hybrid approach that combines item-based collaborative filtering with content-based methods yielded the most effective predictions. This research provides valuable insights for the practical implementation of recommender systems tailored to banking savings products.

The remainder of this paper is structured as follows: The Literature Review section discusses the fundamental concepts, methodologies, and algorithms of recommendation systems, along with relevant literature and previous research in the field. The Research Method section describes the architecture and methodology of our recommendation system. The Dataset section outlines the data sources, preprocessing techniques, and characteristics of the banking transaction data used. The Implementation and Result section presents the experimental procedures and analyzes the performance of different recommendation models. The Discussion section interprets the results and highlights their practical implications, and finally, the Conclusion section summarizes the contributions and suggests directions for future research.

2. Literature review

In this section, we review key concepts and prior research related to recommendation systems. The implementation methods of recommendation systems can be broadly classified into three main categories: *collaborative filtering, content-based filtering, and hybrid approaches.*

Collaborative filtering (CF) relies on past user-item interactions, typically structured as a rating matrix. The core assumption is that users with similar preferences will rate items similarly. This allows the system to recommend items based on shared interests among users (Wang, 2014; Aggarwal, 2016; Ajaegbu, 2021). A key advantage of this method is that it does not require item content and features, enabling accurate recommendations even for complex items. However, it faces notable challenges: (a) the ***cold-start problem***, where insufficient data exists for new users or items (Aggarwal, 2016); (b) ***scalability***, as large systems must process data for millions of users and items (Papadakis, 2021), (c) ***sparsity***, since users typically interact with only a small portion of the available items (Wang, 2014).

CF method is classified into memory-based and model-based approaches. The memory-based approach calculates similarity between users or items based on interactions (Oyebode, 2020; Papadakis, 2021), including user-based CF (Papadakis, 2021; Sharaf, 2022; Wang, 2014) and item-based CF (Ajaegbu, 2021; Xue, 2019) Model-based methods apply machine learning to identify patterns in user behavior (Jena, 2022; Aljunid, 2021; Chen, 2021).

Content-based method generates recommendations by analyzing a user's historical preferences and item features (Aggarwal, 2016). It compares new items to those previously liked, using shared attributes to compute similarity (Pazzani, 2007; Javed, 2021; Kumar, 2014). This approach offers advantages such as independence from other users, transparency, and the ability to suggest novel items. However, it may suffer from limited recommendation diversity, often failing to suggest unexpected yet relevant items (Aggarwal, 2016; Achakulvisut, 2016; Javed, 2021).

Hybrid methods combine these approaches, often blending collaborative and content-based filtering to improve accuracy and overcome individual limitations (Aljunid, 2021; Sharaf, 2022). These models aim to provide more balanced and robust recommendations by integrating the strengths of each technique.

A significant amount of research has been conducted over the past decades. During this time, these methods have been successfully applied in various domains, such as movie recommendations (Jena, 2022; Wang, 2014), hotel rooms recommendations (Hu, 2024; Shambour, 2022), and articles, publications, and news recommendations (De Gemmis, 2015; Achakulvisut, 2016; Pashigorev, 2025) among others. While significant research has been conducted over the past decades, the application of recommendation systems in the financial sector, such as for bank products and services, remains limited. Temitope et al. (2020) introduced a graph-based recommender system for financial products. Additional research in this domain includes a systematic literature review by Wu and Li (2025), which examines recent approaches to financial product recommendation and proposes a framework distinguishing financial product recommendations from other domains. Furthermore, Barreau and Carlier (2021) proposed a collaborative filtering approach by incorporating the temporal context of user-item interactions to provide dynamic financial recommendations.

Oyebode and Orji (2020) developed a hybrid recommender approach for financial products by combining item-based collaborative filtering with customer demographic data. Gorgoglione and Panniello (2011) developed a customer churn prediction model to identify at-risk customers. The study explored a recommendation-based approach to propose personalized retention actions. By leveraging the behaviors of similar loyal customers, the bank implemented efficient solutions to enhance customer retention through targeted product recommendations. Klioutchnikov et al (2020) introduced a recommendation system designed for financial intermediaries. Its primary objectives are to provide personalized filtering of financial information, support decision-making for financial intermediaries, and analyze financial consumers' behavior and habits to propose optimal solutions.

Despite these advancements, the implementation of recommendation systems in financial services is still not widespread, partly due to unique challenges within the sector, as discussed by Ghiye et al (2023). However, there is a scarcity of studies focusing on recommendation systems for banks' savings products.

3. Research method

In this section, we present the research methodology used in the study. We have adapted the concepts, including formulas, to align with banking savings products. Before delving into the research methodology in detail, here we explain the fundamental concepts, notions, and calculations relevant to the methodology.

3.1. Customer-Product rating matrix

Consider a set of customers $C = \{c_1, c_2, \ldots, c_n\}$ and a set of products $P = \{p_1, p_2, \ldots, p_m\}$ where n represents the total number of customers and m represents the total number of products. The customer-product rating matrix is structured as an $m \times n$ matrix, where each entry r_{ij} corresponds to the rating assigned by customer c_j to product p_i, for $1 \leq i \leq m$ and $1 \leq j \leq n$.

3.2 Cosine similarity measure

In this study, we employed the cosine similarity measure to quantify the similarity between users and products (Singh, 2020). In the context of recommendation systems, cosine similarity is widely used in CF to determine the similarity between users (user-based CF) or between products (item-based CF) (Aljunid, 2021). Cosine similarity calculates the cosine of the angle between two non-zero vectors in a multi-dimensional space, producing a similarity score ranging from -1 to 1. A score of 1 implies that the vectors are perfectly aligned, indicating maximum similarity; a score of 0 denotes orthogonality, implying no similarity; and a score of -1 indicates that the vectors are opposed.

3.3 Predict rating

This section describes the rating prediction for unrated products using user-based CF, item-based CF, and content-based methods.

In user-based CF, the predicted rating that a customer would assign to an unrated product is estimated by analyzing the ratings provided by other customers with similar preferences. Specifically, the method identifies a group of customers who exhibit similar rating patterns to the target customer. It then computes a weighted average of the ratings these similar customers have given to the product in question, where the weights are determined by the degree of similarity between the customers. The more similar a customer is to the target customer, the greater influence their rating has on the final prediction (Aggarwal, 2016).

In item-based CF, the prediction of a customer's rating for an unrated product is based on the customer's past ratings of similar products. Instead of focusing on customers with similar behavior, this method examines the relationships between products. The system identifies products that are similar to the target product and that the customer has previously rated. It then estimates the predicted rating by calculating a weighted average of the customer's ratings for these similar products, where the weights reflect the degree of similarity between the products. As a result, products that are more similar to the target product have a stronger impact on the final prediction (Aljunid, 2021).

In the content-based method, the system predicts a customer's rating for a new product by analyzing the attributes or features of products the customer has previously interacted with. The assumption is that customers tend to prefer products that share similar attributes with those they liked in the past. To make a prediction, the system evaluates how closely the target product matches previously rated products based on their content features. Ratings for these previously interacted products are combined, giving more weight to those with higher similarity. This technique is useful in domains where explicit feedback is limited but product attributes are well-defined (Achakulvisut, 2016), such as in the banking sector.

3.4 The architecture of research methodology

The core stage of our hybrid method is integrated predicted ratings from *user-based* and *item-based CF*, along with a content-based approach. For a target customer, each product's predicted rating is combined with its corresponding average rating using a weighted approach. The steps of our recommendation approach consisted of the following:

1. First, create a customer-product rating matrix from customer rating data.
2. Predict the ratings using the CF approach. It has the following stages:
   a. ***Construct the similarity matrix.*** In user-based CF, the similarity between users is calculated based on their rating patterns, while in item-based CF, the similarity between items is determined using customer ratings. This process results in the creation of both user

similarity and product similarity matrices, which are computed using the cosine similarity measure.

b. ***Predict rating scores*** for products the customer has not yet rated by utilizing ratings from similar customers or products.

3. Predict the ratings using the content-based approach**.** It has the following stages:

a. ***Transform product attributes***. We transformed the attributes of savings products into numerical data using feature engineering techniques. One-Hot Encoding (Lopez-Arevalo, 2020) was used to convert categorical variables into binary vectors, enabling their use in machine learning models. The process involves three main steps: first, identifying all unique categories within a categorical column; second, creating a separate binary column for each unique category; and third, assigning a value of 1 to the column corresponding to the category of each row while setting all other columns to 0.

b. ***Create the similarity matrix***. After transforming the product attributes into a numerical vector, we calculated the similarity matrix of the products using cosine similarity.

c. ***Predict ratings***. The predicted rating for an unrated product is calculated as a weighted sum of the customer's past ratings, with the weights determined by the similarity scores between the products.

4. Predict the ratings using the hybrid approach**.** The predicted rating for an unrated product is estimated by taking the weighted sum of the content-based and CF rating scores. The weights are controlled by α (content weight) and $1-\alpha$ (collaborative filtering weight), ensuring their sum is 1. This approach follows the principle of a weighted average.

$$\text{Hybrid rating} = \alpha \times \text{Content-based rating} + (1-\alpha) \times \text{CF rating} \qquad \text{(Eq. 1)}$$

5. Recommend *top N* products for target customer *c*. Select *top-N* products ordered in descending order of the combined ratings for all products for the target customer *c*.

4. Dataset

This research is based on collected data from a well-established bank in Mongolia, covering savings products and customer usage between 2021 and 2023. The dataset includes the following:

1. Customers' transaction (utility) data of savings products. This dataset contains the records of customer interactions with savings products. Initially, it included transaction data for 1,000 customers. However, after the data cleansing process, we excluded 383 customer records due to the absence of any savings product usage over the three years. As customers do not provide explicit ratings for banking products, we infer ratings from their transaction data. This transaction data includes customer ID, product name, and the number of product purchases, which serve as customer rating data in our recommendation method. To protect privacy, customer IDs and Product names were anonymized. The number of product purchases represents the number of new agreements a customer has signed with the bank to acquire a savings product,

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while extensions of existing savings product terms are not considered purchases. In our dataset, the total number of products purchased by each customer ranged from 1 to 5. Given that the data set covers three years, this range was considered reasonable. We determined it to be suitable for defining the customer rating scale and used these values as customer ratings without applying any transformation or normalization. A sample of product ratings data is presented in Table 1.

Table 1. Product ratings dataset (sample)

Customer ID	Product ID	Rating
1002	P2	1
1002	P3	3
1002	P4	2
1002	P7	2
1002	P25	3
1300	P1	4
1300	P2	1
1300	P7	3
1300	P25	1
1001	P11	1
1001	P13	2
1001	P24	1
1017	P4	5

2. Product profile data. This contains details of the bank's savings products, such as the minimum deposit amount, interest rates, interest pre-payment options, and terms of the savings product. The bank offers 26 different savings products. However, after data preprocessing, we merged products that were essentially the same but had different names for marketing purposes, reducing the total number to 19. The sample product profile data, presented in its original and transformed formats, is shown in Table 2 and Table 3, respectively.

Table 2. Product profile data (before transformation)

Product ID	Interest rate (Per year)	Minimum deposit (MNT)	Interest pre-payment options	Possibility of obtaining a loan secured by a deposit	Incurring expenses during the interim period	Terms of the savings products
P1	9.5%	10000	Not allowed	Yes	No	3 months
P2	10.5%	20000	Allowed	Yes	No	6 months
P3	11.0%	20000	Allowed	Yes	No	9 months

Table 3. Transformed product profile data

Product ID	Interest 9.5%	Interest 10.5%	Interest 11%	…	Min 10000	Min 20000	…	Interest pre-payment options	Terms 3 month	Terms 6 month	...
P1	1	0	0	…	1	0	…	0	1	0	...
P2	0	1	0	…	0	1	…	1	0	1	...
P3	0	0	1	…	0	1	…	1	0	0	...

5. Implementation and Result

We implemented our hybrid recommender methodology, as described in Sect. 3.4, using Python. Our product ratings dataset consists of 877 entries. To assess the system's predictive accuracy, we conducted several experiments. In the following subsections, we provide an overview of the experimental setup, evaluation metrics, results, and *top N* recommendations.

5.1 Experimental design

To evaluate the performance of our methodologies, we conducted experiments and compared the prediction accuracy of user-based and item-based collaborative filtering, the content-based approach, and the hybrid methodology. Before running the experiments, we partitioned our product ratings dataset into training and test sets, using 30% of each customer's ratings for testing, while the remaining 70% was used for training. Using the training set, we generated the customer-product rating matrix and similarity matrices for user and item similarity based on customer ratings, as well as the item similarity matrix based on product attributes. Our dataset consists of 660 entries in the training set and 217 entries in the test set.

5.2 Evaluation metrics

To assess the accuracy of our predictions, we utilize three error metrics: RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error). These metrics evaluate the discrepancy between predicted and actual values.

- RMSE is the square root of MSE, maintaining the same unit as the original ratings and making it easier to interpret.
- MAE calculates the average absolute difference, providing a more direct measure of prediction error without emphasizing larger deviations.

Each metric provides a different perspective on model performance, helping to balance sensitivity to outliers and interpretability. The formulas of metrics are given as follows:

$$RMSE = \sqrt{\frac{\sum_{r_{c,p} \in Dtest} (\hat{r}_{c,p} - r_{c,p})^2}{N}} \qquad \text{(Eq. 2)}$$

$$MAE = \frac{\sum_{r_{c,p} \in Dtest} |\hat{r}_{c,p} - r_{c,p}|}{N} \quad \text{(Eq. 3)}$$

where D_{test} is the test set used for evaluation, $r_{c,p}$ is the actual rating given by customer c for product p in the test set, and $\hat{r}_{c,p}$ is the predicted rating for product p by customer c. N is the number of entries in the test set.

5.3 Experimental results

In this section, we present our experiments and the corresponding results. Our experiments were conducted following the stages outlined in the research methodology architecture described in Section 3.4. The experimental process consists of the following steps:

1. We implemented two CF approaches: user-based filtering and item-based filtering, generating predicted customer ratings.
2. In the second stage, we applied the content-based method to generate predicted customer ratings.

The effectiveness of our recommendation approaches can be assessed using RMSE and MAE on the test set. Lower values indicate better predictive accuracy. Table 4 presents the RMSE and MAE values for the different recommendation models.

Table 4. Values of evaluation metrics of the rating prediction

	RMSE	MAE
User-based CF	1.769	1.542
Item-based CF	1.651	1.399
Content-based method	1.282	0.965

From Table 4, we can observe that the item-based model performs better than the user-based model, with lower RMSE (1.65 vs. 1.77) and MAE (1.40 vs. 1.54), indicating that recommendations based on item similarities generalize better to new data than those based on user similarities. As RMSE gives more weight to larger errors, the slightly higher RMSE of the user-based model indicates that it occasionally produces larger prediction inaccuracies. Meanwhile, MAE provides a more direct measure of how much predictions deviate from actual ratings. The content-based approach achieved the lowest RMSE (1.28) and MAE (0.97), demonstrating its effectiveness in generating accurate recommendations (Table 4). The consistently superior performance of the content-based approach highlights the importance of leveraging product attributes and customer preferences over CF methods for banking savings product recommendations.

3. In the third stage of our experiment, we implemented the hybrid approach by combining collaborative filtering and content-based methods using a weighted approach. The hybrid

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rating score was computed according to Eq. 1. We tested 11 different α values, ranging from 0.1 to 0.95, and evaluated error metrics for both user-based CF hybridization and item-based CF hybridization (Table 5).

From Table 5, we observe that increasing α, thereby assigning more weight to content-based filtering, leads to a steady decrease in RMSE and MAE, confirming its positive impact on prediction accuracy. The optimal performance is achieved at α = 0.85, where these error metrics reach their lowest values, demonstrating the effectiveness of a well-balanced combination of two approaches.

Table 5. Evaluation of hybrid models with varying α values

α	Hybrid (α *Content-based + (1- α) *User-Based CF)		Hybrid (α *Content-based + (1- α) *Item-Based CF)	
	RMSE	MAE	RMSE	MAE
0.1	1.670	1.434	1.569	1.310
0.2	1.578	1.327	1.495	1.227
0.3	1.495	1.223	1.429	1.151
0.4	1.422	1.137	1.372	1.091
0.5	1.361	1.069	1.325	1.038
0.6	1.313	1.038	1.290	1.015
0.7	1.281	1.010	1.268	0.996
0.8	1.264	0.992	1.259	0.986
0.85	1.260	0.986	1.260	0.980
0.90	1.265	0.978	1.260	0.981
0.95	1.271	0.971	1.271	0.969

Among the individual models, the content-based approach delivers the highest accuracy, achieving the lowest RMSE and MAE. The hybrid model further enhances prediction accuracy, with α = 0.85 proving to be the most effective balance, reinforcing the dominant role of content-based filtering in improving recommendations.

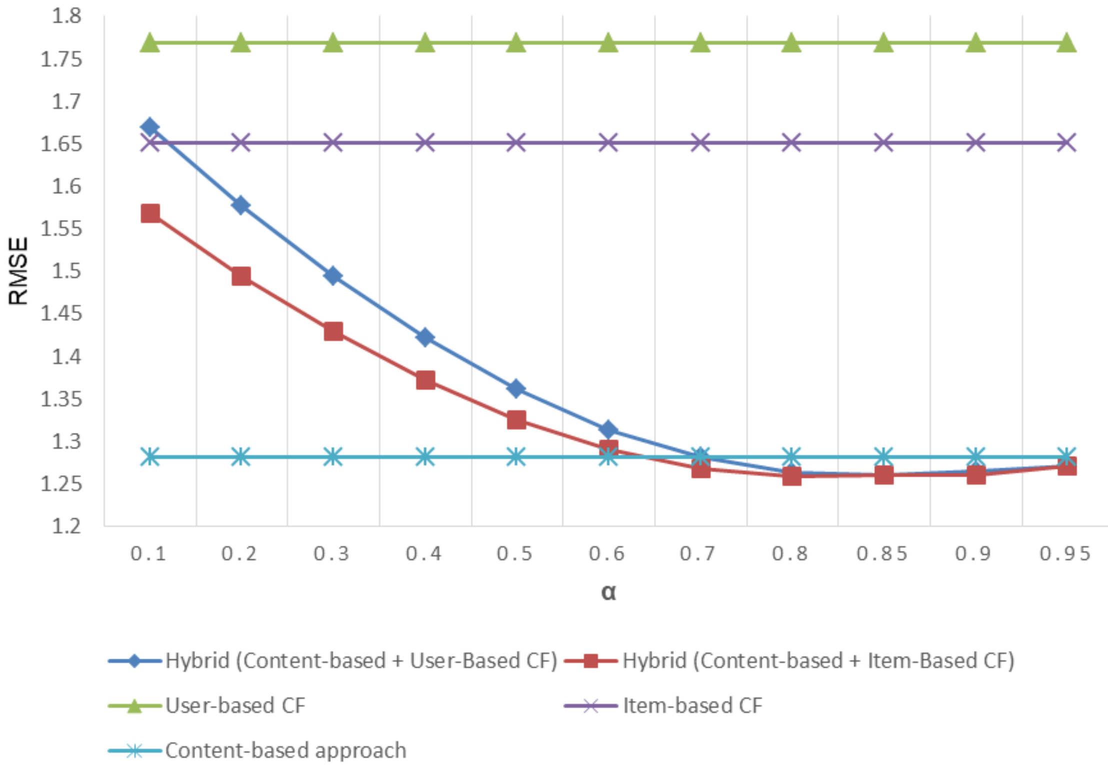

Figure 1. RMSE of the approaches

5.4 Top-N recommendations

To recommend products to target customer *c*, the system first extracts this information from the customer-rating matrix, identifying which products the user has previously interacted with. The recommendation process focuses on generating rating scores only for new (unseen) products that the customer has not interacted with before. If either method does not provide a rating score for a given item, it is assumed to be 0. After computing the hybrid rating scores for all items, the system selects the *top N* highest-rated products for recommendation. However, products that the customer has previously purchased are excluded from the recommendations to ensure they receive only new and relevant suggestions.

5.5 Discussion

The results of this study indicate that the content-based recommendation method outperforms other individual approaches for banking savings products. However, a content-based approach alone may limit product discovery for customers, as they are primarily recommended products similar to those they have already interacted with. By incorporating item-based CF, the hybrid model enhances personalization and increases recommendation diversity. Notably, hybrid models improve accuracy, with $\alpha = 0.85$ yielding the best results, emphasizing the significance of content-based filtering.

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One of the characteristics of banking savings products is that customers do not simply purchase them for consumption but rather generate future income. Consequently, they make decisions based on product attributes rather than behavioral patterns. While the hybrid model does not significantly outperform the content-based approach in predictive accuracy, it effectively balances the strengths and weaknesses of both methods, ultimately delivering more personalized recommendations to customers.

Conclusion

In this study, we compared the predictive performance of collaborative filtering, content-based, and hybrid approaches for generating personalized recommendations to enhance savings product sales in the banking sector. Our methodology introduced an algorithm to derive implicit ratings from transaction data.

The results indicate that when the content-based weight is $\alpha = 0.85$, the hybrid model outperforms both standalone content-based and collaborative filtering methods. By leveraging the advantages of both techniques, the hybrid model delivers highly personalized recommendations for both existing and potential customers. This research successfully validates that content-based and hybrid approaches are not only scalable and efficient but also practical and feasible for real-world banking applications. By implementing a recommender system, banks can increase the variety of savings products available to customers, expand financial resources, and mitigate risks associated with funding sources. As the next step, we plan to conduct an online experiment in a real banking environment, where selected customers will receive personalized product recommendations. Their feedback will be systematically collected and analyzed to refine and enhance the recommendation quality. This iterative approach will help optimize personalization strategies based on evolving customer preferences and behaviors.

Building on the findings of this study, several future research directions may be pursued to enhance the accuracy and personalization of recommendations. First, incorporating demographic information (e.g., age, income level, financial goals) into the model could improve its ability to understand user preferences, thereby increasing the relevance of recommendations. Such data would allow the system to tailor suggestions not only based on past interactions but also on broader user characteristics.

Our proposed hybrid model has a key limitation that it does not directly address cold-start scenarios where new users lack historical interaction data. To mitigate this issue, the model can be extended by integrating a demographic-based pre-filtering layer. This would enable the system to provide initial recommendations by grouping users based on similar demographic profiles and drawing on content features of highly-rated products within those cohorts. Furthermore, combining demographic data with content-based attributes in a hybrid demographic-content framework could facilitate reasonably accurate predictions for new users, ensuring relevant suggestions even before sufficient behavioral data becomes available.

Second, instead of relying on a static weighting scheme, future research could explore adaptive weighting techniques, such as reinforcement learning or Bayesian optimization. These methods could dynamically adjust the hybrid weight parameter (α) in response to user engagement and feedback, allowing the system to adapt more effectively to individual user behavior over time.

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