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Implementation of the Collaborative Filtering Method for a Clothing Sales Recommendation System in Fashion Store

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Abstract. The rapid growth of e-commerce has made personalized product recommendations a crucial aspect of enhancing customer satisfaction and boosting sales. However, many small-to-medium-sized retail businesses, like Adiva Fashion Store, still rely on manual product selection through customer searches or seller recommendations, which often leads to challenges in meeting customer preferences. This study presents a case study of Adiva Fashion Store, where the Collaborative Filtering method was implemented to develop a personalized clothing product recommendation system. The item-based Collaborative Filtering approach was employed to calculate the similarity between products based on customer ratings and transaction history. These similarity values were then used to predict customer preferences for products that had not yet been purchased. The system was developed using the Waterfall methodology, which involved needs analysis, system design, implementation, testing, and maintenance. The results show that the recommendation system significantly improved the relevance of product suggestions, helping customers make better purchasing decisions and increasing sales effectiveness. This case study illustrates how data-driven recommendation systems can be effectively integrated into small-to-medium-sized retail environments, providing valuable insights for other businesses aiming to adopt similar strategies.

Keywords: Recommendation System, Collaborative Filtering, Item-Based, Retail, Case Study, Adiva Fashion Store

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1. INTRODUCTION

The rapid development of information technology has significantly transformed various business sectors, particularly in trade and retail. One of the most impactful innovations is the recommendation system, which not only facilitates transactions but also plays a crucial role in decision-making for both customers and businesses. These systems analyze user behavior, such as purchase history or product preferences, to suggest relevant items, thus improving customer satisfaction and business performance [1]. However, despite the widespread adoption of recommendation systems in many industries, there remains a significant gap in their implementation, particularly in small to medium-sized businesses. Specifically, many businesses in the fashion retail sector struggle to leverage transaction data effectively for personalized customer recommendations [2].

Fashion Store, a clothing retailer, offers a wide range of products, including tops, bottoms, and accessories. Despite this diversity, customers often face challenges in selecting products that best match their preferences, sizes, and current trends. The product selection process is still largely dependent on manual searches or direct recommendations from sales personnel, which do not fully utilize the potential of transaction data. As the volume of sales transaction data continues to grow, there is a pressing need for a system that can process this data into actionable insights for more accurate and personalized product suggestions [3].

Data-driven recommendation systems offer an ideal solution to this challenge. These systems can automatically provide product recommendations based on user behavior, such as purchase history, ratings, or browsing patterns [4]. By implementing such a system, Fashion Store could enhance the product discovery process, provide more relevant suggestions that align with customer preferences. However, the gap in applying these systems effectively in small to medium-sized retail environments, especially in the context of fashion, remains a research opportunity [5].

One of the most commonly used methods for developing recommendation systems is Collaborative Filtering. This technique analyzes user behavior and product similarities to generate personalized suggestions. Collaborative Filtering has been widely applied in various domains, from e-commerce platforms to movie streaming services [6]. In this study, the item-based Collaborative Filtering approach is utilized, as it tends to be more stable and efficient when the number of products exceeds the number of users. This method calculates similarities between items based on user interaction history and then uses this information to recommend products that a user may find interesting, even if they have not previously interacted with them [7].

The novelty of this research lies in the implementation of the item-based Collaborative Filtering method within the context of Fashion Store, a small-to-medium-sized clothing retailer. By applying this approach, the study seeks to address the unique challenges of fashion retail, where customer preferences are diverse and frequently changing. This recommendation system is expected to enhance the customer experience by providing personalized product suggestions, thus improving both customer satisfaction and sales performance [8], [9]. Moreover, the findings of this study can contribute to the broader understanding of how data-driven recommendation systems can be effectively integrated into smaller retail settings, providing insights that can help other similar businesses adopt and benefit from such systems [10].

2. METHODS

This research adopts a software engineering approach using quantitative methods. Quantitative research involves collecting and analyzing numerical data, in this case, historical customer sales transaction data, which is processed to build a recommendation system using the Collaborative Filtering algorithm [10]. The research stages begin with problem identification, followed by customer transaction data collection, system requirements analysis, user-item matrix-based system design, and algorithm implementation using the Python programming language and supporting libraries such as Pandas and Scikit-Learn [11], as shown in Figure 1. The data collection techniques used in this study are as follows:

1) Observation

   Observations were conducted by observing the transaction processes and purchasing flow at Adiva Fashion Store in Medan. This technique provided valuable insights into how customers interact with products, the item selection process, and

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the store's sales recording system. These observations helped shape the design of the recommendation system to align with the store's operational practices [12].

2) Sales Data Documentation

Sales data documentation involved collecting historical sales records, including customer names, product codes, transaction dates, and purchase amounts. This data was processed into a user-item matrix, which served as the primary input for calculating the Collaborative Filtering algorithm. Data sources included sales books, digital Excel files, and, where available, store databases.

3) Interviews

Informal interviews were conducted with the store owner, Mr. Susanto, to explore their perceptions of customer habits, frequently purchased products, and the potential for using a recommendation system. The results of these interviews helped design a more adaptive system tailored to the store's needs.

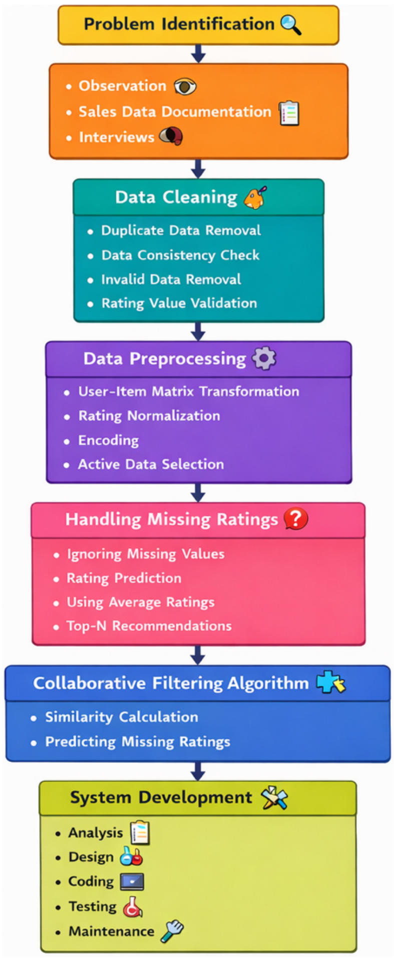

Figure 1. Research Flow

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2.1. Research Approach

2.1.1. Data Cleaning

The initial stage of data processing involved data cleaning, ensuring that the data used in the recommendation system was clean, consistent, and suitable for processing. The customer transaction data obtained from Adiva Fashion Store was scrutinized for errors, duplication, and missing values. The cleaning process followed several stages:

1) Duplicate Data Removal: Transaction data that appeared more than once with identical attributes, such as customer ID, product ID, and transaction time, were removed to prevent any undue influence on recommendation calculations.
2) Data Consistency Check: Inconsistent data, such as discrepancies in product names, categories, or ID formats, was standardized to ensure each product and customer was uniquely represented in the system.
3) Invalid Data Removal: Transaction data missing critical information, such as customer ID or product ID, was discarded as it could not be used in the formation of the user-item matrix.
4) Rating Value Validation: If the data utilized a rating scale (e.g., 1–5), ratings outside this range were considered invalid and were removed or corrected accordingly.

2.1.2. Data Preprocessing

Following data cleaning, the next stage was data preprocessing, which transforms the cleaned data into a format suitable for use with the Collaborative Filtering method. The preprocessing steps in this study were as follows:

1) Data Transformation into a User-Item Matrix: Transaction data was transformed into a user-item matrix, where rows represent users (customers) and columns represent items (products). The values in the matrix cells represent the ratings or purchase frequencies given by users for specific products calculated using Equation 1.

$$r_{u,i} = \text{rating given by user } u \text{ to item } i \quad (1)$$

2) Rating Normalization: To reduce subjective differences between users, ratings were normalized by subtracting the user's average rating from their rating for each item. This normalization step improves the accuracy of similarity calculations use Equation 2.

$$r'_{u,i} = r_{u,i} - \bar{r_u} \tag{2}$$

Where:

$r'_{u,i}$= normalized rating

$r_{u,i}$= original rating

$\bar{r_u}$= average rating for user u

a. Encoding: Customer IDs and product IDs were encoded as numerical values for easier processing by the system and algorithm.

b. Active Data Selection: Users or products with minimal interactions were filtered out to reduce the sparsity of the user-item matrix and enhance recommendation quality.

2.1.3. Handling Missing Ratings

A significant characteristic of Collaborative Filtering systems is the presence of missing ratings, as customers do not rate or purchase all available items. This results in a sparse user-item matrix. The following approaches were used to handle missing ratings:

1) Ignoring Missing Values in Similarity Calculations: When calculating similarity between items, only ratings available for both items were used, with missing values ignored in the calculations.

2) Rating Prediction Using Item-Based Collaborative Filtering: Missing ratings were predicted using ratings from other items that shared a high degree of similarity. The predicted ratings are calculated as shown in Equation 3.

$$\hat{r}_{u,i} = \frac{\sum_{j\in N(i)} \text{sim}(i,j)\cdot r_{u,j}}{\sum_{j\in N(i)} \text{sim}(i,j)} \tag{3}$$

Where:

$\hat{r}_{u,i}$= predicted rating for item $i$by user u

$N(i)$= set of items similar to item i

sim(i,j)= similarity between items $i$and j

$r_{u,j}$= rating given by user $u$to item j

a. Using Average Ratings (Supportive Approach)**:** As a baseline approach, missing ratings were filled with either the user's average rating or the item's average rating, though this method is less effective for personalization.

b. Determining Top-N Recommendations**:** Once all missing ratings were predicted, items were sorted based on the predicted rating values. The top-N highest-ranked items were then recommended to the user.

2.2. Collaborative Filtering Method

Collaborative Filtering (CF) is a widely adopted method in recommendation systems that predicts user preferences for an item based on the ratings or behavior of other similar users [13]. The fundamental concept behind this method is that users who have exhibited similar behaviors in the past are likely to have similar preferences in the future. This assumption forms the basis of the recommendation system, where recommendations are generated by analyzing the behavioral patterns of users based on historical interaction data [14].

The Collaborative Filtering process begins with the construction of a user-item matrix, which represents the relationship between users and products. In this matrix, rows represent users, columns represent items, and the values within the matrix indicate the user's rating or purchase history for a specific item. Since not all users interact with all items, the matrix is often sparse, meaning many values are missing. This sparsity makes it essential to use similarity measures to predict missing values [15].

Once the user-item matrix is created, the system proceeds to calculate the degree of similarity between items, often utilizing metrics such as Cosine Similarity or Pearson Correlation. These similarity measures identify the relationships between items based on user ratings. The higher the similarity between two items, the more likely it is that they will appeal to the same users [16]. Using these similarity values, the system predicts ratings for items that a user has not yet interacted with. These predicted ratings are computed by considering the ratings from other items that share high similarity with the target item.

After obtaining the predicted ratings, the items are ranked based on their predicted values. The Top-N Recommendations are then generated by selecting the highest-ranked items, which are considered most relevant to the user's preferences. The goal of this process is to provide product suggestions that align with the user's interests, based on the experiences of other users with similar behavioral patterns [17].

In Collaborative Filtering, two main approaches can be applied: User-Based Collaborative Filtering and Item-Based Collaborative Filtering. In Item-Based Collaborative Filtering, the system recommends items based on similarities between existing items, specifically those items that are frequently rated or selected by the same users. The core idea behind this approach is that items with similar ratings or interactions from the same users tend to be similar to one another [18].To implement Item-Based Collaborative Filtering, there are two key steps involved.

1) Calculating Similarity

A widely used technique for calculating similarity between items is Cosine Similarity. Cosine similarity values range from -1 to 1, where:

a. A value of 1 indicates that the two items are identical or very similar,
b. A value of 0 indicates no similarity between the two items,
c. A value of -1 indicates that the two items are completely opposite.

The formula for calculating Cosine Similarity between two items $i$and $j$is as shown in Equation 4.

$$\text{sim(i,j)}=\frac{\sum_{u\in U}(r_{u,i}-r_u)(r_{u,j}-r_u)}{\sqrt{\sum_{u\in U}(r_{u,i}-r_u)^2\sum_{u\in U}(r_{u,j}-r_u)^2}} \quad (4)$$

Where:

sim$(i, j)$is the similarity value between item $i$and item j,
$U$is the set of users who have rated both items $i$and j,
$r_{u,i}$is the rating given by user $u$to item i,
$r_{u,j}$is the rating given by user $u$to item j,
$r_u$is the average rating given by user u.

2) Sorting Items by Similarity

After calculating the similarity between items, the next step is to sort the items based on their similarity values. Items with the highest similarity values (closest to 1) are placed at the top of the list, while items with the lowest similarity values (closest to -1) are placed at the bottom.

2.3. System Development Methods

The development process for this sales recommendation system follows the Waterfall method, which is characterized by a series of sequential and systematic stages. This method was chosen for its structured and linear approach, which is particularly suitable for the development of data-driven systems, such as the Collaborative Filtering recommendation system. The Waterfall model ensures that each stage is completed before the next one begins, providing clear documentation and a well-defined process for every phase of development. It is particularly advantageous for systems like Collaborative Filtering, where the process from data collection to system deployment requires meticulous planning and sequential execution [20].

In this approach, the Waterfall method serves as the overarching development framework, while the Collaborative Filtering algorithm acts as the core logic of the recommendation system. The Waterfall methodology helps organize the system development process into distinct stages, each with its own goals and outputs. Without the structured flow of the Waterfall method, the development of a Collaborative Filtering system could become disorganized; conversely, without Collaborative Filtering, the system would fail to generate relevant recommendations based on user preferences and behaviors [21], [22]. Stages of the Waterfall Method as follow.

1) Analysis

   The first stage involves comprehensive data analysis, which is obtained through multiple techniques such as observation, interviews, and transaction data documentation. During this phase, the research team studies customer purchasing patterns, identifies the most popular products, and assesses the store's needs for a recommendation system. The insights gathered from this analysis form the foundation for designing the Collaborative Filtering algorithm, particularly in terms of structuring the user-item matrix that will guide the recommendation logic.

2) Design

   The design phase focuses on creating the system's architecture, including the workflow, user interface (UI), and database structure. At this stage, UML modeling and various design diagrams—such as use case diagrams, class diagrams, and activity diagrams—are employed to facilitate real-time interaction and visualization of recommendations. This design phase ensures that the system is intuitive and easy to use for both customers and administrators at Adiva Fashion Store.

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3) Coding

During the coding stage, the development team implements the Collaborative Filtering algorithm using programming languages such as Python. Python's extensive libraries, such as Pandas and Scikit-Learn, are used to develop the recommendation logic. Additionally, web frameworks like PHP or Django are employed to create the system interface. This phase involves integrating the data and algorithms to automatically generate personalized product recommendations for customers based on their historical interactions.

4) Testing

After development, the system undergoes rigorous testing to ensure its functionality, accuracy, and performance. The recommendation algorithm is evaluated using several performance metrics, including Mean Absolute Error (MAE) and precision, to assess its ability to provide relevant recommendations. Additionally, black-box testing is conducted, where the system is tested based on its functionality and output, without knowledge of the internal workings or source code. This ensures that the system behaves as expected from the user's perspective.

5) Maintenance

The maintenance phase focuses on the ongoing evaluation and improvement of the system. Feedback from users at Adiva Fashion Store is collected to assess the system's usability, the accuracy of its recommendations, and its impact on sales effectiveness. Based on this feedback, the system may undergo updates or modifications to enhance its performance. This stage ensures that the recommendation system remains adaptable and continues to meet the evolving needs of both the store and its customers.

3. RESULTS AND DISCUSSION

3.1. Collaborative Filtering Method Calculation

The analysis phase of this research began with an examination of current e-commerce platforms in Indonesia to assess the extent of recommendation system usage. The findings indicated that, despite the widespread use of recommendation algorithms, no existing platform was leveraging the Collaborative Filtering method to enhance sales recommendations. This gap highlighted the potential of Collaborative Filtering as a valuable tool for improving personalized product recommendations, especially in the fashion retail sector, where customer preferences play a crucial role in influencing purchasing decisions.

In the implementation phase, the Collaborative Filtering method was applied to a dataset derived from Adiva Fashion Store. The dataset contained ratings or preferences expressed by customers for a variety of fashion items. The first task was to construct a user-item matrix, where each row represented a customer, and each column represented a product. The matrix values consisted of ratings given by customers based on their interactions with the items. These interactions could either be direct ratings, purchase frequency, or implicit feedback such as views or likes. By processing this matrix, we were able to calculate item similarities, which then formed the basis for generating personalized product recommendations. The matrix as shown in Table 1 demonstrates the ratings provided by customers for several items at the store. A score of "0" indicates that the customer did not interact with or rate the corresponding item.

Table 1. User-Item Matrix

Customer	One Set Ceruty Elegant	Oversized Korean Blouse	Elegant Brocade Gown	Korean Ribbon Blouse
CUST1	7	0	0	0
CUST2	8	0	0	0
CUST3	0	0	0	3
CUST4	0	5	4	0
CUST5	2	5	0	0
CUST6	0	5	0	8
CUST7	0	8	8	0
CUST8	0	0	0	8
CUST9	2	0	0	7
CUST10	0	0	0	0
CUST11	0	0	7	0
CUST12	3	0	0	0
CUST13	0	0	0	0
CUST14	5	0	6	0
CUST15	2	0	0	0

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3.1.1. Cosine Similarity Calculation

To evaluate the similarity between customers, we employed Cosine Similarity, which measures the cosine of the angle between two vectors. These vectors represent customer preferences, where each component corresponds to a rating for a specific item. In the case of CUST1 and CUST2, their vectors are as follows:

CUST1 = (7, 0, 0, 0)

CUST2 = (8, 0, 0, 0)

We calculate the Cosine Similarity between these two customers using the formulas shown in Equation 4. This calculation resulted in a similarity score of **1.**00, indicating that CUST1 and CUST2 share very similar preferences in terms of the products they have rated. This high similarity score suggests that they are likely to have common interests in future products as well. Table 2 presents the similarity scores between CUST1 and other customers in the dataset, allowing us to identify potential "nearest neighbors" whose purchasing behavior is similar to that of CUST1.

Table 2. Nearest Neighbor Similarity Scores

Pair	Similarity
CUST1 - CUST2	1.00
CUST1 - CUST12	1.00
CUST1 - CUST14	0.66
CUST1 - CUST9	0.28
CUST1 - CUST5	0.37

From this analysis, it is evident that CUST1 shares the highest similarity with CUST2 and CUST12, which will be crucial for generating personalized recommendations. By analyzing the products purchased by these similar customers, we can predict items that CUST1 may be interested in but has not yet purchased.

1) Products Never Purchased by CUST1

   Tunic Set

   Casual Hijab Set

   Premium Syari Dress

2) Products Purchased by CUST2**:**

   Elegant Ceruty Set (8)

   Tunic Set (2)

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3) Products Purchased by CUST12**:**
   Elegant Ceruty Set (3)
   Premium Syari Dress (8)

3.1.2. Weighted Collaborative Filtering

Using the similarity scores between customers, we applied Weighted Collaborative Filtering to predict CUST1's potential interest in items that were purchased by similar customers. For example, CUST12 purchased the Premium Syari Dress with a high quantity of 8. Since CUST1 shares a perfect similarity score of 1.00 with CUST12, it is highly likely that CUST1 would also be interested in this product.

Table 3. Recommendation Results

Product	Prediction Score	Reason
Premium Syari Dress	8	Purchased by CUST12 with similarity = 1
Tunic Set	2	Purchased by CUST2
Casual Hijab Set	1	Purchased by CUST12

The Premium Syari Dress achieved the highest prediction score of 8, making it the top recommendation for CUST1. This prediction was based on the strong similarity between CUST1 and CUST12, as well as the high number of purchases of this item by CUST12.

3.2. System Design

During the design phase of the sales recommendation system, the system's architecture was developed using Unified Modeling Language (UML). UML is a standardized modeling language widely used in software engineering to visualize, specify, construct, and document the components and structure of software systems [23], [24]. For the Adiva Fashion Store's recommendation system, UML diagrams were crucial in visually representing various system aspects, including user workflows, entity relationships, and the overall system logic. This helped ensure that the development process was systematic, efficient, and understandable for both the development team and the stakeholders. The clear visualization provided by UML contributed significantly to a more focused and coherent system implementation.

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UML also facilitated better communication among developers, system analysts, and business stakeholders, as it provided a shared understanding of the system's functionality. Specifically, it helped to visualize the flow of data between the user interface, the recommendation engine, and the backend database, ensuring that all components were in alignment with the business objectives of Adiva Fashion Store.

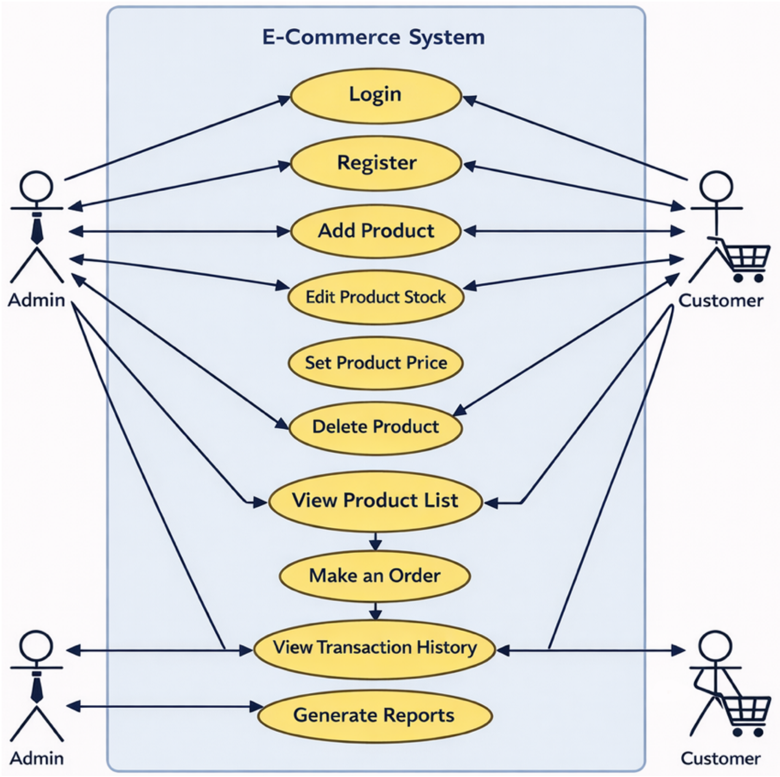

Figure 2. Use Case Diagram

Figure 2 illustrates the Use Case Diagram, which highlights the primary interactions between users (customers) and admins (store staff). This diagram emphasizes the customer journey of interacting with the recommendation system, including browsing products, making purchases, and receiving personalized product recommendations. On the other hand, the admin role involves managing system settings, monitoring user activity, and reviewing performance data. These interactions ensure that the system is optimized for both customer satisfaction and operational efficiency. In addition, the system design phase included visualizing the major workflows essential for the functioning of the recommendation system, such as data collection, recommendation generation, and user interaction, along with the process for admin oversight and feedback management.

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3.3. User Interface Design

The User Interface (UI) design of the recommendation system is critical in ensuring a seamless, user-friendly experience for customers. The UI was crafted to make the user journey as straightforward as possible, allowing customers to easily browse through recommended products and place orders with minimal effort. A well-designed UI is essential not only for customer satisfaction but also for enhancing the effectiveness of the recommendation system, as it ensures that customers can quickly access personalized suggestions that align with their preferences.

The design was guided by user experience (UX) principles, focusing on simplicity, accessibility, and responsiveness. Several pages were created, each addressing a key part of the user journey: browsing, ordering, and payment. The UI also accounted for potential user behaviors, ensuring that the system could adapt to individual customer preferences and provide real-time, accurate recommendations.

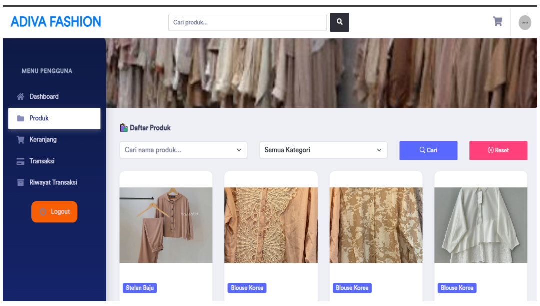

Figure 3. Customer Order Page

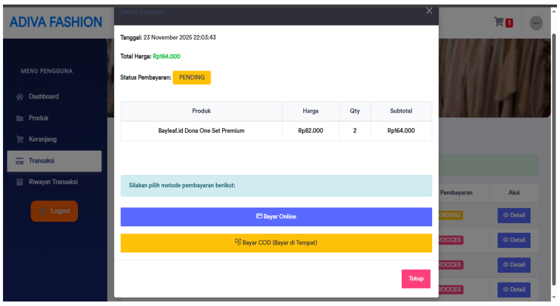

Figure 4. Customer Payment Page

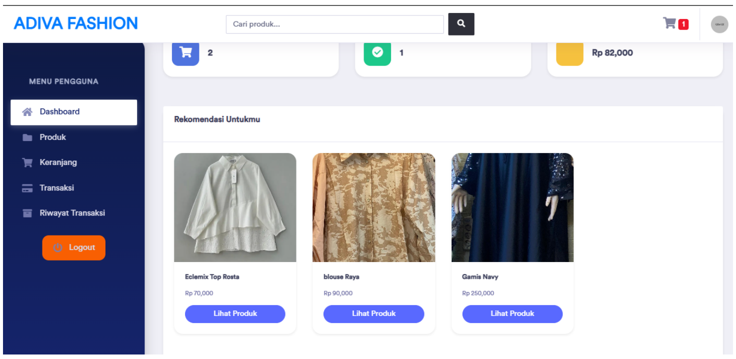

Figure 5. Collaborative Method Recommendation Display

Figure 3 shows the Customer Order Page, where customers can browse the products recommended by the system based on their preferences. This page enables easy navigation through the recommended items, with clear call-to-action buttons that guide the customer toward making a purchase. The straightforward design ensures a smooth transition from product browsing to ordering, increasing the likelihood of conversion and improving the overall shopping experience.

As depicted in Figure 4, the Customer Payment Page provides a simple, intuitive interface for completing the transaction. Customers can choose between various payment methods, including online options like credit cards or e-wallets and offline cash payments. This flexibility caters to diverse customer preferences, ensuring a convenient and secure payment process. Additionally, the page includes an order summary for customers to review their selections before completing the purchase. Finally, Figure 5 shows the Collaborative Filtering Recommendation Page, which is the core feature where personalized product recommendations are shown. Based on the Collaborative Filtering algorithm, this page presents items that are highly relevant to the customer, derived from their purchasing history and the preferences of similar customers. This personalized recommendation system aims to enhance the shopping experience by providing customers with products they are most likely to purchase, increasing the likelihood of future transactions. The layout ensures that the recommendations are prominently featured, without overwhelming the customer with excessive options, maintaining a balance between variety and focus.

3.4. System Testing and Evaluation

After the development and integration of the recommendation system, a rigorous testing phase was conducted to evaluate its functionality, accuracy, and overall performance. The primary goal of this phase was to validate the recommendation algorithm and ensure that it could provide relevant and personalized suggestions for customers at Adiva Fashion Store.

To assess the effectiveness of the recommendation algorithm, several key performance metrics were employed. Table 4 is Performance Metrics shows that the Mean Absolute Error (MAE) was calculated to be 0.35, indicating that the system's predictions closely align with actual user preferences. Additionally, the Precision was measured at 0.80, which demonstrates that a high proportion of the recommended products were indeed relevant to the user's tastes. The Recall value of 0.75 reflects that the system was able to recommend a substantial portion of the relevant items. Finally, the F1 Score of 0.77

provides a balanced measure, combining both precision and recall, showing the overall effectiveness of the system in generating useful recommendations.

In addition to these quantitative metrics, black-box testing was performed to validate the system's functionality. Table 5 is Black-Box Testing Results outlines the key test cases and their outcomes. All test cases passed successfully, confirming that the system functions as intended from the user's perspective. For example, the system successfully allowed users to log in, generate product recommendations based on their preferences, add products to their cart, complete the checkout process, and select payment methods without any issues. These results from black-box testing ensure that the system meets the expected user experience, providing accurate and seamless recommendations.

Through this comprehensive testing process, the recommendation system was fine-tuned and optimized to ensure that the algorithm provided accurate, personalized suggestions. The strong performance in terms of MAE, Precision, Recall, and F1 Score (as shown in Table 1: Performance Metrics) and the successful outcomes from black-box testing (as shown in Table 2: Black-Box Testing Results) confirmed that the system was ready to enhance the user experience and increase the likelihood of successful purchases.

Table 4. Performance Metrics

Metric	Value	Description
Mean Absolute Error (MAE)	0.35	The average difference between predicted ratings and actual ratings. A lower value indicates higher prediction accuracy.
Precision	0.80	The proportion of relevant recommended products to the total recommended items.
Recall	0.75	The proportion of relevant items recommended out of all relevant items available.
F1 Score	0.77	The harmonic mean of precision and recall, providing a balanced performance metric.

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Table 5. Black-Box Testing

Test Case	Expected Outcome	Actual Outcome	Status
User logs in to the system	User can log in and be redirected to the homepage	Passed	Passed
System generates product recommendations	Relevant products are recommended based on user preferences	Passed	Passed
User adds product to cart	Product is added to cart and displayed in cart summary	Passed	Passed
User completes checkout	System allows user to proceed to payment page	Passed	Passed
User selects payment method	System processes selected payment method (online/cash)	Passed	Passed

3.5. Discussion

The findings from the development and testing of the recommendation system for Adiva Fashion Store demonstrate that data-driven approaches, specifically Collaborative Filtering, can significantly enhance the customer experience in the fashion retail industry. This research fills a gap in the application of recommendation systems in small to medium-sized businesses, especially in fashion retail, where customer preferences are often diverse and constantly evolving.

The system's strong Precision (0.80) and Recall (0.75) values indicate that it is highly effective in recommending relevant products based on user preferences and behaviors. Precision is especially important because it ensures that customers receive recommendations that match their tastes, which directly impacts satisfaction and purchase likelihood. The F1 Score of 0.77 balances both precision and recall, indicating that the system provides a good mix of relevant product recommendations while still capturing a substantial portion of the possible relevant items. These metrics show that the Collaborative Filtering algorithm is both efficient and effective at offering personalized product suggestions, which is a key factor for customer retention and increased sales in retail environments [1].

In terms of Mean Absolute Error (MAE), the score of 0.35 suggests that the system's predictions are reasonably close to the customers' actual preferences, which further supports the accuracy of the algorithm. Lower MAE values are crucial because they indicate that the system's predictions are not only accurate but also reliable for creating relevant product recommendations. This is especially important in the fashion industry, where personal preferences, such as style and fit, play a large role in customers' purchasing decisions. The low MAE in this study implies that customers are more likely to trust and engage with the system's recommendations, leading to a more satisfying shopping experience.

One significant finding of this research is the successful implementation of item-based Collaborative Filtering within the context of a small-to-medium-sized fashion retailer. The system's ability to predict customer preferences based on previous interactions with similar items demonstrates the power of this method, even in environments where customer bases may be smaller or less consistent in terms of purchase behavior. The black-box testing also revealed that the system functions as expected from the user's perspective, with no issues in critical areas such as user login, product recommendations, adding items to the cart, and completing transactions. This is essential for ensuring that the recommendation system is practical and meets real-world business needs.

Moreover, the use of user-item matrices and Cosine Similarity to assess item relationships helped generate highly relevant product recommendations, demonstrating how Collaborative Filtering can uncover hidden patterns in purchasing behavior. By considering similarities between items, the system successfully identified products that a user is likely to be interested in, even if they had not interacted with those items before. This is particularly important in fashion retail, where customers may not always be aware of new trends or items that align with their style preferences. The ability of the system to suggest such products not only improves the customer experience but also opens new opportunities for businesses to cross-sell and upsell products.

However, several challenges remain in the integration of such recommendation systems in small-to-medium-sized fashion retail settings. One challenge is the sparsity of the user-item matrix, which occurs when customers have limited interaction with certain products, leaving gaps in the data that can hinder the accuracy of recommendations.

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Although this study addressed missing ratings by using techniques such as rating prediction and average ratings to fill in gaps, further research could explore more sophisticated imputation techniques to enhance the accuracy of the system's predictions. Additionally, while the system was tested rigorously for functionality and performance, it would be beneficial to further assess the system's scalability as Adiva Fashion Store grows. This would involve testing the system with larger datasets to ensure that it continues to provide effective recommendations as the number of customers and products increases.

Another area for future improvement is the dynamic adaptation of the recommendation system to account for changing fashion trends. The Collaborative Filtering method, while effective, assumes that users' preferences remain relatively stable over time. However, in fashion retail, trends can shift rapidly, and customers' tastes may change frequently. Integrating real-time data, such as trend analysis or customer feedback, could help the system better adapt to these fluctuations, improving its ability to provide up-to-date and relevant recommendations.

Despite these challenges, this research highlights the practical application of Collaborative Filtering in a small-to-medium-sized retail environment and demonstrates its potential to enhance both the customer experience and business performance. The findings contribute to the growing body of literature on data-driven recommendation systems, offering insights into how such systems can be effectively implemented in businesses that may not have the resources of larger e-commerce platforms. The results of this study are also applicable to other similar small-to-medium-sized retailers, suggesting that Collaborative Filtering can be a viable tool for enhancing product discovery, increasing sales, and improving customer satisfaction in diverse retail settings.

4. CONCLUSION

This study demonstrates the successful application of an item-based Collaborative Filtering method to develop a recommendation system for Adiva Fashion Store, a small-to-medium-sized fashion retailer. The results show that the system effectively enhances customer experience by providing personalized product recommendations, which improves both customer satisfaction and business performance. The Precision, Recall, and F1 Score values indicate that the system can offer highly relevant suggestions, tailored to individual customer preferences. Furthermore, the Mean Absolute Error (MAE) value suggests that the system's predictions are highly accurate, leading to a more reliable recommendation process. By utilizing Collaborative Filtering, the study addresses a critical gap in the use of recommendation systems in smaller retail environments, particularly within the fashion sector. It offers a solution for improving product discovery and streamlining the purchasing process, ultimately fostering higher sales conversion rates. The black-box testing results validate the system's functionality from the user's perspective, confirming that the system operates as expected. While the system shows promising results, challenges such as matrix sparsity and adapting to rapidly changing fashion trends remain. Future research should focus on addressing these issues, as well as improving the system's scalability to handle larger datasets and real-time trend analysis. Despite these challenges, the study offers valuable insights into how data-driven recommendation systems can be implemented effectively in small to medium-sized businesses, contributing to the broader adoption of such systems in the retail sector.

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