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Original Research

Optical Marketplace and POS Integration Based on Content-Based Filtering

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ABSTRACT

Manual transaction management in optical businesses often results in stock data discrepancies, delays in report preparation, and limited marketing reach. This study aims to develop an optical marketplace integrated with a Point of Sales (PoS) system to synchronize transaction and stock data in real-time. In addition, a Content-Based Filtering algorithm is implemented with binary product attribute weighting and customer preference profiles based on transaction frequency, combined with multi-channel Cosine Similarity calculations to generate product recommendations based on product characteristics and customer purchase history. The study was conducted through the stages of needs analysis, system design, implementation, and functional testing using the Black-box Testing method. The results show that the integration of the marketplace and PoS successfully maintains the consistency of transaction and stock data, while the Content-Based Filtering algorithm is able to provide product recommendations that match customer preferences. This study shows that the integration of the marketplace, Point of Sales, and recommendation systems can support the digitalization of optical businesses through more efficient data management and an improved customer shopping experience.

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1. INTRODUCTION

Digital transformation is encouraging various business sectors, including the optical industry, to shift from manual work methods to digital systems to increase the speed, accuracy, and efficiency of business processes [1]. The use of web-based sales information and stock management systems has been proven to make operations more efficient, expand markets, and support better business decisions through transaction data recorded in real time [2]. In the retail and e-commerce industry, the implementation of online sales and marketplace systems has been proven to be able to speed up the transaction process and increase the competitiveness and growth of MSME businesses [3].

Optik Fiqri, a MSME specializing in optical sales and services, still processes sales, inventory records, and reports manually using notebooks and Microsoft Excel. This leads to inconsistencies in inventory data, delays in sales reports, and difficulty monitoring customer favorite product trends. Research in various MSME sectors, such as hardware stores, printing shops, and tire shops, shows that digitizing sales and inventory systems can improve data accuracy, speed up service, and significantly reduce human error [4]. In addition, sales are still limited to direct transactions in stores, making Optik Fiqri's marketing reach less than optimal, even though the implementation of sales websites and marketplaces has been proven to be able to expand the market and increase business competitiveness [5].

Several previous studies have discussed these relevant aspects separately. For example, the implementation of a Point of Sales system in a food and beverage retail business [6], reported that computer-based POS can improve operational efficiency and stock accuracy because every sales transaction is automatically recorded and immediately reduces the amount of stock [1]. However, these systems generally stand alone without being connected to online sales channels, so stock and sales data between physical stores and e-commerce platforms can potentially be out of sync. On the other hand, research on product recommendation systems on e-commerce platforms has implemented many Content-Based Filtering and Hybrid Filtering approaches based on customer purchasing patterns and product attributes, showing that Content-Based Filtering is effective when user data is limited, as it recommends products based on similar content features without requiring numerous user ratings [7]. Recent trends in recommendation systems are moving towards a multichannel or hybrid approach, where multiple product attributes and information channels such as content descriptions, categories, and transaction history are weighted differently to increase the relevance of recommendations, while reducing the problems of overspecialization and data sparsity [8].

Although marketplaces, Point of Sales systems, and Content-Based Filtering algorithms have each been extensively researched, research integrating all three into a single platform, particularly in the optical sector, is still rare [9]. Research on website-based sales and inventory information systems generally focuses on automating transaction recording, stock management, and reporting [10], while the study of product recommendation systems focuses more on improving the accuracy of recommendations in an e-commerce environment without direct integration with POS modules and stock management. The novelty of this research lies in the integration of marketplaces and Point of Sales systems into one integrated platform equipped with a Content-Based Filtering algorithm with a multi-attribute weighting scheme, so that different product attributes and transaction channels can be weighted according to their contribution to the relevance of recommendations, specifically designed for optical MSMEs with limited user data characteristics.

Based on these research problems and gaps, this study aims to integrate an optical marketplace and a Point of Sales system based on a Content-Based Filtering algorithm. The developed system is expected to automatically align transaction data, stock, and sales reports between offline and online channels, expand sales reach through digital platforms, and generate more relevant product recommendations based on customer history and preferences.

2. RESEARCH METHODS

2.1. Data Collection Stage

This research was conducted using a case study of Optik Fiqri, a small and medium-sized enterprise engaged in optical sales and services. Currently, sales processes, stock recording, and reporting at Optik Fiqri are still carried out manually using notebooks and Microsoft Excel. Therefore, this research aims to develop a system that can support these business processes digitally.

The initial stage of the research began with information gathering from books and scientific journals. This was done to understand the basic concepts of marketplaces, sales processes, and existing recommendation systems. Furthermore, the research involved direct observation at optical stores. These observations covered the process of recording products, transactions, and how product recommendations are provided to customers.

The research also involved interviews with optical store owners or managers. The purpose of these interviews was to understand their needs for the system to be developed. This study provided a more comprehensive picture of how marketplaces, points of sale, and recommendation systems operate, as well as how Content-Based Filtering and Cosine Similarity could be applied in this context.

2.2. Research Design

This research uses the Waterfall system development model, which consists of sequential stages of requirements analysis, system design, implementation, and testing. This model was chosen because the system requirements were clearly defined from the beginning of the research through observations and interviews, allowing each stage to be implemented systematically.

The research design describes the steps in the research process from beginning to end, including system development and testing. The research process begins with data collection and system requirements analysis. Based on the analysis, a system design was developed, including database design, business processes, and application structure as guidelines for the implementation process.

After the design process was completed, the optical marketplace system was installed, connected to the Point of Sales (POS) system, and a Content-Based Filtering algorithm was implemented to provide product recommendations to users. The system implementation was built using two integrated platforms. The marketplace section was developed using the Next.js framework, while the dashboard and backend of the system were developed using the CodeIgniter 4 framework. The two platforms are connected via an API, which connects to a single database to ensure synchronization of transaction data, stock, and sales reports between the marketplace and the Point of Sales system. The technology selection was based on its suitability for the development needs of an integrated marketplace and Point of Sale system. The final step was testing the system to ensure all features function smoothly and accurately according to the specified requirements [11–15].

2.3. Content-Based Filtering Method

The Content-Based Filtering method is used to recommend products by comparing product characteristics and user interaction history. Each product is represented by several attributes, such as frame type, material, frame shape, color, size, brand, price, and usage type.

Product attribute weighting is done binary (1 if the product has the attribute, and 0 otherwise), while the user preference profile is formed from the accumulated transaction frequency (term frequency) of previously purchased products, excluding the inverse document frequency component. This profile produces two vectors: User Vector (overall transaction history) and POS Vector (physical store-specific transaction history). The similarity between vectors is calculated using Cosine Similarity:

$$\text{Similarity}(A, B) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \tag{1}$$

The system applies the Weighted Multi Channel CBF approach, where the final recommendation score is a linear combination of three cosine similarity values — CBF Score (product viewed vs candidate), User Score (User Vector vs candidate), and POS Score (POS Vector vs candidate):

$$S = w_1 S_b + w_2 S_u + w_3 S_p \tag{2}$$

Where S is the final recommendation score, S_b, S_u, and S_p are respectively the cosine similarity values between the candidate product and the base product (CBF Score), user profile (User Score), and POS transaction profile (POS Score), while w_1, w_2, and w_3 are the weights of each component with the following conditions:

- $w_1 = 0.40; w_2 = 0.40; w_3 = 0.20$ — if the user has a history of POS transactions.
- $w_1 = 0.40; w_2 = 0.60; w_3 = 0.00$ — if the user only has an online transaction history.

To provide a clearer picture of the above process, the flowchart of the Content-Based Filtering recommendation system is presented in Figure 1.

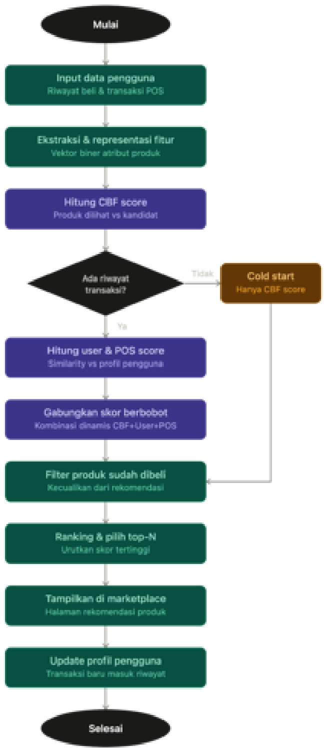

Figure 1. Flowchart of the Content-Based Filtering recommendation process

2.4. Testing Method

System testing is conducted to ensure all system functions operate according to established requirements. The method used is Black-Box Testing, which focuses solely on existing functions without examining the system's internal components or program code. Testing is conducted on key features such as account login, product search, sales process, payment, inventory management, and product recommendation features.

In addition to functional testing using Black-Box Testing, the accuracy of the recommendations generated by the Content-Based Filtering algorithm is also tested. This testing aims to measure the level of relevance between the system's recommended products and user preferences based on purchase history. Testing is conducted using precision and recall methods, comparing the number of relevant products successfully recommended to the total number of recommended products and to the total number of relevant products available.

3. RESULTS AND DISCUSSION

3.1. Implementation Results

An optical marketplace integrated with a Point of Sale (POS) was successfully implemented on a web-based basis. The system has two user types: admin/cashier and customer. The integration between the marketplace and POS automatically synchronizes product data, stock, transactions, and purchase history, ensuring that the information displayed on the marketplace always reflects available stock. The system implementation interfaces are shown in Figures 2 through 5 [16–18]:

3.1.1. Home Page Marketplace

Figure 2 shows the main page of the optical marketplace, which serves as the initial interface for customers. This page provides a list of products, categories, a search feature, and product recommendations, making it easier for users to find products that meet their needs.

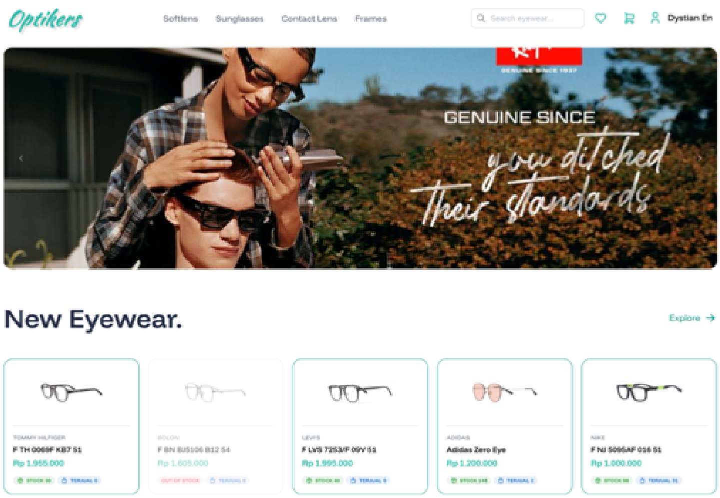

Figure 2. Marketplace Home Page

3.1.2. Recommendation Section

Figure 3 shows the product recommendation feature implemented using a Content-Based Filtering algorithm. The system provides recommendations based on product characteristics similar to the user's previous purchases, thus better aligning the product with the user's tastes and desires.

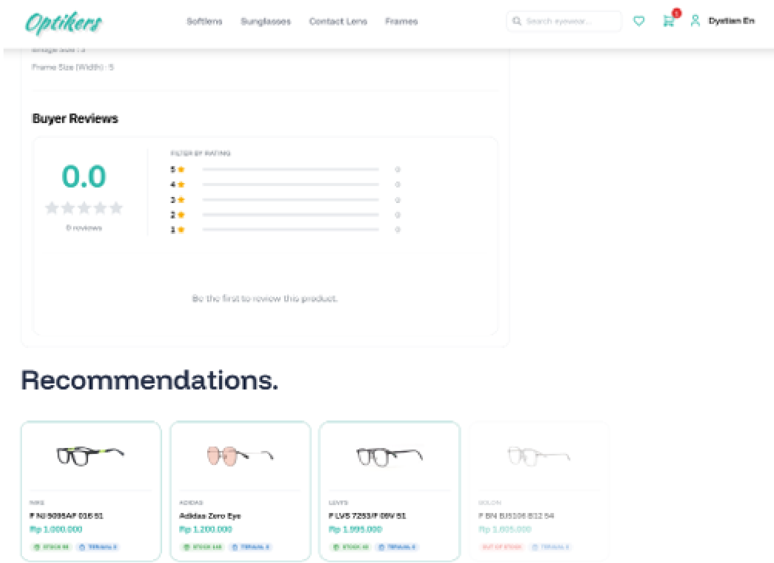

Figure 3. Recommendation Section

3.1.3. Dashboard and Data Management

Figure 4 shows the admin dashboard, which presents a summary of transaction, product, and customer data as an operational control center. Through this dashboard, admins can manage product and stock data; any changes to product or stock data are immediately reflected in the system, ensuring that marketplace information remains consistent with physical stock levels. Additionally, sales reports are available, displaying transaction details, sales volume, and total revenue for business evaluation purposes.

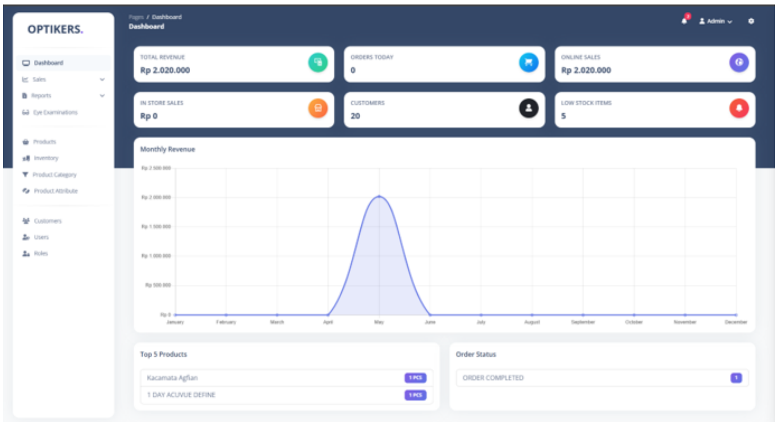

Figure 4. Dashboard Page

3.1.4. Point of Sales

Figure 5 shows the Point of Sales transaction page used by cashiers to process in-store purchases. Every successfully processed transaction is stored in the same database as the marketplace, ensuring that sales data remains connected and integrated.

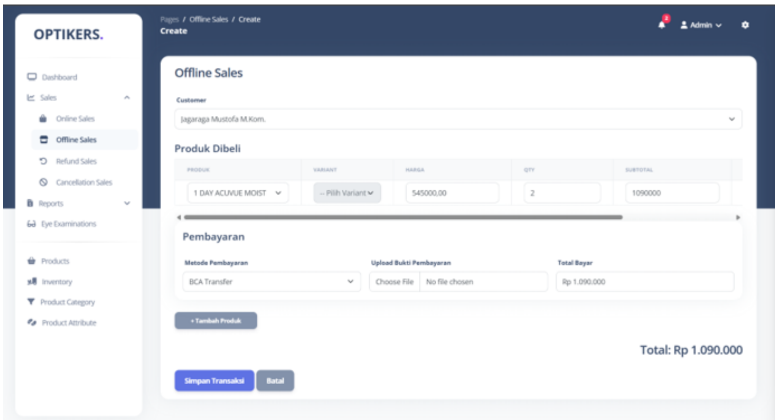

Figure 5. Point of Sales

3.2. Data Integration Test Results

This testing aims to verify that transaction and stock data between the marketplace and Point of Sale are consistently synchronized through a single, unified database. The testing is conducted by simulating transactions from both platforms and observing any data changes that occur [19, 20]. The results are summarized in Table 1.

Table 1. Data Integration Test Results

No	Scenario	Initial Conditions	Actions	Final Condition
1	PoS transactions reduce marketplace stock	Stock "Gucci GG1891O" = 150 units	Cashier sells 2 units at PoS	Stock of "Gucci GG 1891 O" in the marketplace = 148 units
2	Marketplace transactions reduce PoS stock	Stock "Ray Ban GG12212F" = 50 units	Customer purchased 1 unit online	Stock of "Ray Ban GG12212F" on the admin/PoS dashboard = 49 units
3	Product data update by admin	Price of "1 Day Acuvue Define" = 1,000,000	Admin changes product price/description	Changes appearing in the marketplace = 1,200,000

Based on the test results in Table 1, all data integration scenarios between the marketplace and Point of Sales demonstrated consistent results as expected. Stock changes resulting from transactions, both offline at the Point of Sale and online through the marketplace, were synchronized automatically and in real time through a single, integrated database. Similarly, product data changes made by the admin were immediately reflected in the marketplace without delay. This demonstrates that the designed integration architecture is capable of maintaining data consistency across platforms.

3.3. Functional Testing Results (Black-Box Testing)

The core capabilities of the system were evaluated through functional Black-Box testing procedures. The summary of testing scenarios and responses is presented in Table 2.

Table 2. System Functional Test Results

No	Tested Features	Testing Scenario	Method	Results
1	Register & Login	Users register and log in using valid and invalid data.	Black-box Testing	The system successfully authenticates and displays an error message for invalid data.
2	Optical Marketplace	Displays product list, search and product filter	Black-box Testing	Products are displayed according to the data and filters selected by the user.
3	Content-Based Filtering Recommendations	Displays recommendations based on user profile and transaction history	Black-box Testing	The system successfully displays products with a level of relevance according to user preferences.
4	Point of Sales (PoS)	Conduct sales transactions offline	Black-box Testing	Transaction is successfully saved, stock is updated, and data is synchronized with the marketplace.

Based on testing results, all of the system's main functions functioned according to their functional requirements. The marketplace feature effectively displayed products and performed searches, while the Content-Based Filtering algorithm successfully provided recommendations based on product characteristics and user shopping history. Furthermore, integration with the cashier system enabled automatic updating of transaction and stock data, ensuring data consistency between the marketplace and the cashier system.

3.4. Recommendation Algorithm Results (Content-Based Filtering)

The product recommendation feature is implemented using a multi-channel Content-Based Filtering (Weighted Multichannel CBF) approach. The final recommendation score is calculated from a combination of three cosine similarity scores: similarity to the currently viewed product (CBF Score), similarity to the user's overall preference profile (User Score), and similarity to the user's transaction profile in a physical store (POS Score). Tests were conducted under three different conditions to demonstrate how this algorithm performs in a real-world system.

3.4.1. Cold Start Condition

The first condition was tested on users with no transaction history whatsoever. The results are shown in Table 3.

Table 3. Recommendation Results in Cold Start Conditions

Rank	Product	Match Specs	CBF Score	User Score	POS Score	Final Score	Status
1	GG1891O (Gucci, Rp 9.676.000)	5/9	0.5893	0.0000	0.0000	0.2357	Recommended
2	GG12212F (Ray Ban, Rp 1.000.000)	4/9	0.5040	0.0000	0.0000	0.2016	Recommended
3	1 Day Acuvue Define (Acuvue, Rp 1.000.000)	1/9	0.2357	0.0000	0.0000	0.0943	Recommended

The data in Table 3 is obtained from the Personalized Recommendation Debug page, which displays the details of the dot product calculation and the magnitude of each vector in real time, allowing for transparent verification of the score calculation process. In this condition, the User Score and POS Score are 0.0000 for all candidate products because the user has no transaction history, so the Final Score is entirely determined by the CBF Score multiplied by its weight. Product GG1891O obtained the highest CBF Score (0.5893) with a match of 5 out of 9 attributes, thus ranking first with a Final Score of 0.2357.

3.4.2. Condition with Complete Transaction History

The second condition was tested on users with both online and offline (POS) transaction histories. The results are shown in Table 4.

Table 4. Recommendation Results with Complete Transaction History

Rank	Product	Match Specs	CBF Score	User Score	POS Score	Final Score	Status
1	William Morris; Bond (BL); AC1 (BLK) PZ-51 (Morris, Rp 3.000.000)	6/9	0.6667	0.5213	0.3536	0.5459	Recommended
2	Spyder; Pilot 2; 3S000 (BLK) PZ-00 (Rayban, Rp 1.300.000)	4/9	0.4444	0.4518	0.3536	0.4292	Recommended
3	Progear; S1284; 4 (BLU)-57 (Prog, Rp 2.200.000)	4/9	0.4444	0.2433	0.1179	0.2987	Recommended

In this condition, all three score components — CBF Score, User Score, and POS Score — are all greater than 0 and contribute to the Final Score according to equation (2). The product "William Morris; Bond (BL); AC1 (BLK) PZ-51" obtains the highest Final Score (0.5459), which is obtained from the calculation $(0.40 \times 0.6667) + (0.40 \times 0.5213) + (0.20 \times 0.3536) = 0.5459$, according to the dynamic weights $w_1 = 0.40$, $w_2 = 0.40$, and $w_3 = 0.20$ applied when the user has a POS transaction history. This result proves that the Weighted Multichannel CBF approach works as designed, by considering the similarity of product attributes as well as user preferences from two transaction channels simultaneously.

3.4.3. Filtering Rules for Products Already Purchased

The third condition tests the filtering rules for products that have already been purchased by the user. The results are shown in Table 5.

Table 5. Results of Filtering Products That Have Been Purchased

No	Rank	Product	Match Specs	CBF Score	User Score	POS Score	Final Score	Status
1	-	GG1891O (Gucci, Rp 9.676.000)	5/9	0.5893	0.8847	1.0000	0.7896	Filtered
2	-	GG12212F (Ray Ban, Rp 1.000.000)	4/9	0.5040	0.5911	0.2673	0.4915	Filtered
3	-	1 Day Acuvue Define (Acuvue, Rp 1.000.000)	1/9	0.2357	0.3686	0.2500	0.2917	Filtered

Although the three products in Table 5 have varying Final Scores — even the highest at GG1891O (0.7896) due to the combination of high User Score and POS Score — the system still marks all three as Filtered because they are recorded in the user's purchase history. This demonstrates that the filtering rules operate independently of the similarity score, preventing repeated product recommendations to the same user.

Based on the test results in Tables 3, 4, and 5, the multi-channel Content-Based Filtering algorithm is proven capable of adapting its recommendation strategy to the availability of user data: relying independently on product attribute similarity during cold start conditions, weighting the three score components when transaction history is available, and applying business rules to avoid repeated recommendations. Thus, the system's recommendations are more personalized and adaptive than conventional Content-Based Filtering approaches that only compare product similarity.

3.5. Discussion

The findings of this study demonstrate that integrating an optical marketplace with a Point of Sales (PoS) system, augmented by a Weighted Multichannel Content-Based Filtering (CBF) algorithm, effectively addresses the operational and marketing challenges faced by optical MSMEs. Unlike previous studies that implemented standalone POS systems [6] or isolated e-commerce recommendation modules [7], this research successfully bridges the online-offline divide. The real-time synchronization of inventory and transaction data ensures data consistency, eliminating the discrepancies and reporting delays inherent in manual recording methods. This aligns with the broader digital transformation goals for MSMEs, proving that unified database architectures can significantly enhance operational transparency, stock accuracy, and managerial decision-making [1, 10].

From an algorithmic perspective, the implementation of the Weighted Multichannel CBF approach offers a novel solution to the limitations of traditional recommendation systems. Standard Collaborative Filtering often struggles with the "cold start" problem due to a lack of historical user rating data [7]. In contrast, this study's system gracefully handles cold start conditions by relying entirely on product attribute similarity (CBF Score), ensuring that new users still receive relevant and logical recommendations. Furthermore, the inclusion of a "POS Score" represents a significant novelty. Most conventional e-commerce recommendation systems ignore offline purchase history [8], yet for optical businesses, in-store transactions are strong indicators of customer preference and style. By dynamically weighting the CBF, User, and POS scores ($w_1 = 0.40, w_2 = 0.40, w_3 = 0.20$ for users with complete history), the algorithm adapts to the richness of available user data. This provides highly personalized recommendations that holistically reflect both online browsing behavior and offline purchasing patterns.

The application of business logic, specifically the filtering of previously purchased products, further enhances the system's practical relevance. As demonstrated in Table 5, even when a previously purchased item yields a high similarity score due to strong attribute matching, the system correctly flags it as "Filtered." This prevents redundant recommendations, which is particularly crucial in the optical industry where specific frame or contact lens purchases are typically infrequent and non-repetitive. This rule-based safeguard ensures that the recommendation engine remains commercially viable, avoids user frustration, and improves the overall customer shopping experience.

Despite these promising results, this study acknowledges certain limitations. First, the current CBF model relies on binary attribute weighting, which may oversimplify nuanced customer preferences (e.g., a customer might prioritize a specific brand over frame shape or color). Second, the system was developed and tested within a single MSME case study (Optik Fiqri), meaning its scalability, robustness, and performance under high-concurrency or multi-branch enterprise conditions require further validation. Future research could address these limitations by evolving the system into a Hybrid Filtering model that seamlessly incorporates Collaborative Filtering as the user base and transaction data accumulate. Additionally, integrating computer vision techniques to analyze visual features of optical frames (e.g., automated shape and color extraction from product images) could further refine the content-based similarity calculations, offering an even more robust and visually intuitive recommendation experience for optical retail.

4. CONCLUSION

This study successfully developed and evaluated an integrated optical marketplace and Point of Sales (PoS) system, enhanced by a Weighted Multichannel Content-Based Filtering (CBF) recommendation algorithm. Implemented as a case study at Optik Fiqri, the system effectively addresses the operational inefficiencies of manual record-keeping, such as stock discrepancies and delayed reporting, while simultaneously expanding the business's digital marketing reach.

The empirical results demonstrate two major contributions. First, the unified database architecture ensures real-time, bidirectional synchronization of inventory and transaction data between online and offline channels, maintaining absolute data consistency across platforms as verified by integration and black-box testing. Second, the proposed Weighted Multichannel CBF algorithm proves highly adaptive to varying data availability. It successfully mitigates the cold-start problem by relying on product attribute similarity, and significantly enhances recommendation personalization for existing customers by dynamically weighting online browsing history and offline POS transaction profiles. Furthermore, the implementation of business logic to filter previously purchased items ensures the recommendations remain commercially relevant and non-repetitive.

Overall, this research validates that the convergence of operational management systems (PoS) and intelligent recommendation engines can significantly accelerate the digital transformation of optical MSMEs. For future research, it is recommended to explore the evolution of this system into a Hybrid Filtering model as the user base grows, or to incorporate computer vision techniques for automated visual feature extraction of optical frames, thereby further refining the accuracy and visual intuitiveness of the recommendation system in a multi-branch retail environment.

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Dystian En Yusgiantoro: Conceptualization, Methodology, Software, Data Curation, Writing – Original Draft.
Ari Hidayatullah: Supervision, Validation, Resources, Writing – Review & Editing.

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AI Use Statement:
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