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Using Content-Based Filtering and Apriori for Recommendation Systems in a Smart Shopping System

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ABSTRACT

This research is motivated by the increasing significance of online shopping platforms and the challenges faced by users in locating products that align with their preferences and requirements, which can significantly influence the sales performance of online retailers. Consequently, the primary objective of this study is to design and implement a recommendation system capable of identifying suitable products and forecasting the purchase frequency for various product combinations, while also integrating this recommendation system with a smart shopping platform. To achieve this objective, the research employs machine learning techniques, specifically content-based filtering and the Apriori algorithm. Content-based filtering is utilized to analyze user preferences and behavioral patterns related to visited products, while the Apriori algorithm is employed to evaluate support and confidence values for item set combinations, thereby generating frequency values for future transactions involving product combinations. Additionally, a smart shopping system is developed and integrated, enhancing the shopping experience through smartphone applications and streamlining the payment process to facilitate seamless product purchases. The research methodology involves data collection pertaining to products and user preferences, followed by several testing involving a sample group of user respondents. The results demonstrate that the developed recommendation system effectively delivers relevant product recommendations based on user preferences, achieving a confidence value up to 98%. Furthermore, the smart shopping system proves capable of independently assisting users throughout the transaction process, thereby enhancing overall user experience and convenience.

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1. INTRODUCTION

Technological and information development has transformed the traditional shopping paradigm into an increasingly popular online shopping experience. The convenience of online shopping allows consumers to add products to their shopping carts, make payments using various electronic payment methods, view detailed product information, and conduct product searches. One of the main challenges in online shopping is finding products that match user preferences and needs. In the fast-paced and competitive online shopping environment, users often feel overwhelmed by the abundance of choices and information they must process. Hence, the difficulty in making product choices results in an unsatisfactory shopping experience.

The implementation of recommendation systems provides an effective solution to address these challenges. By analyzing user behavior and preferences, recommendation systems can offer accurate and personalized recommendations for products that are likely to pique the user's interest. This allows users to discover relevant products more quickly and efficiently.

On the other hand, the implementation of the Smart Shopping System has opened up new opportunities to enhance the in-store shopping experience. Leveraging smartphone technology, the Smart Shopping System enables users to access more detailed product information and conduct transactions independently, eliminating the need to wait in line during the checkout process. This provides a connected, intelligent, and integrated shopping experience.

Collaborative filtering and content-based approaches are some of the methods used in building effective recommendation systems. Collaborative filtering leverages user-item interactions and similarities, while content-based methods focus on the intrinsic attributes of products. The synergistic application of these techniques has demonstrated considerable success in mitigating information overload and enhancing user satisfaction in e-commerce platforms (Adomavicius & Tuzhilin, 2005; Faggioli et al., 2020).

Personal recommendations to customers using association rules via the Frequent-Pattern-Growth algorithm were implemented and achieved a high average probability of purchasing the next product (Loukili et al., 2023).

Tessy et al. proposed a recommendation system for property search using a Content-based filtering method. The experiment results show that the system can provide recommendations with more than one keyword user preference (Badriyah et al., 2018).

Mulyana et al. used Content-based filtering and Collaborative Filtering Methods for the recommendation system of product sales ideas for Micro Small Medium Enterprises (MSME). The developed system aims to attract customers' interest while fulfilling the criteria of a micro-enterprise. The testing results achieved were 78% accuracy. This recommendation system can help the community or MSME actors find the appropriate product ideas (Mulyana et al., 2023).

A session-based recommendation system (SBRS) which recommends refinements by inferring product attribute preferences of customers based on the sequence of products viewed earlier in the session was proposed by Akshay et al. AttriBERT is a model that extends BERT architecture to learn from the attribute values of products and a novel product representation strategy, which represents each product as a dictionary of attribute: value pairs (Jagatap et al., 2023).

Multi-dimension Interactions based Knowledge Graph Neural Networks (MI-KGNN) were proposed by effectively extracting both semantic information and structural information in the knowledge graph. Explicit information (i.e., historical user-item interactions) and implicit information (i.e., side information) were utilized in the recommendation system and improved up to 3% compared to the original Knowledge Graph Neural Network (Zilong Wang et al., 2020).

Zhang et al. proposed a sequential recommendation model MGCN4REC based on multi-graph to learn the representation of users and items and then model preferences and instant interests simultaneously. A real data set from Amazon was used in the experiment and the result showed that the proposed method outperforms the current state-of-the-art sequential recommendation methods by over 15% on the metrics (Yan Zhang et al., 2020).

Moreover, the evolution of recommendation systems in e-commerce has witnessed the incorporation of deep learning approaches, contributing to the refinement of personalized suggestions (Salampasis et al., 2023; Wang et al., 2023; Lai & Peng, 2023). Deep learning models, such as neural collaborative filtering, have shown promise in capturing intricate patterns within user behavior and product features, leading to more accurate and relevant recommendations (He et al., 2017)

This research aims to propose innovative and sustainable solutions to enhance the online shopping experience through the integration of Recommendation Systems and the Smart Shopping System. By addressing challenges and capitalizing on existing opportunities, this research has the potential to make a positive contribution to the development of e-commerce and how users shop in the current digital era.

This paper is divided into 4 sections. Section 1 is the introduction of the paper that contains the motivation behind the study. Section 2 is the methodology which covers the object of the study, the effectiveness of the current method, a proposed method that includes Content-Based filtering, and the Apriori algorithm. Section 3 is the result and discussion. Lastly, Section 4 is the conclusion and the future works of the study.

2. RESEARCH METHODOLOGY

This section explains the object of the study and the problem that exists by using the current shopping method. Next, the implementation of Content-Based Filtering and Apriori for optimized online shopping was explained. Then, it was followed by an explanation of the evaluation and validation of the proposed system.

2.1. Object of Study

Aleza, a fashion retailer located in Senayan, Jakarta, is chosen as the object of the study. Aleza is one of the women's clothing retailers located in various cities in Indonesia. It began by providing tailoring services for local fashion brands, and then Aleza created its brand in late 2017. The establishment of Aleza was also based on the needs of Dia Demona, who is the Founder & Creative Director of Aleza and is currently transitioning to wearing hijab. Aleza is a brand under the company PT Moda Trifashindo. Aleza is also one of the local clothing brands that is widely popular among teenagers both in Jakarta and outside Jakarta. Aleza offers several categories of women's clothing, including shirts, tunics, blouses, sweaters, sweatshirts, skirts, pants, dresses, denim, loungewear, accessories, sets, footwear, and scarves. Aleza has 16 stores located in various cities in Indonesia.

Figure 1 illustrates the situation at the Aleza FX Sudirman store when customers are searching for products. It shows a very crowded store situation, and visitors face difficulties in searching for products. Before purchasing a product, customers typically seek compatibility with the product they intend to buy so that the product can be used for an extended period. Customers usually feel more comfortable when using a product that matches the one, they intend to purchase. Additionally, there are some other identified issues.

Figure 1. Aleza retail store

- **Time**: Typically, when customers make a purchase, they want to find related products that match the one they are buying at the moment. However, difficulties in finding suitable related products lead to wasted time for customers in searching for these items. In the current process of searching for related products, customers must go through each section of the store shelves individually, as seen in **Figure 1**.
- **Product Information Management**: In the current transaction process, to view product information, users have to ask store staff. This results in inefficiencies in providing product information to customers.
- **Business Continuity and Technology Adoption**: The limited adoption of advanced technology in the transaction process affects business sustainability. The lack of new customers, especially among young people who are actively using the latest technology, is a concern.
- **Promotion Media**: The limited use of technology in promotion media affects the sales volume of less popular products. By implementing technology media, it is hoped that it can serve as a promotional tool for less popular products.

2.2. Content-Based Filtering

Content-based filtering is a recommendation system technique used in various applications, such as online advertising, e-commerce, and content recommendations on streaming platforms. Its working principle relies on analyzing the characteristics or "content" of items (e.g., articles, products, movies) and matching them to a user's preferences based on their historical behavior or explicit preferences. Below are the four steps of Content-Based filtering.

- **Item representation:** Each item in the system is described using a set of features or attributes. In this study, the features used are product category, brand, price, and customer reviews.
- **User Profile:** The system maintains a user profile that represents the user's preferences or interests. This profile is built based on the user's interactions with items in the past.
- **Feature Matching:** To make recommendations, the system compares the features of items with the user's profile. It calculates a similarity score for each item, indicating how well it matches the user's preferences. Various similarity metrics can be used, such as cosine similarity, Jaccard similarity, or Pearson

correlation, depending on the nature of the features and data. In this study, cosine similarity as shown in Equation 1 is used. Cosine similarity is chosen due to its simple calculation and understanding. The equation is described as follows.

$$\cos(A, B) = \frac{A \cdot B}{\|A\|\|B\|} \tag{1}$$

The expected value is in the range of -1 and 1, where 1 indicates perfect similarity, -1 indicates perfect dissimilarity and 0 indicates orthogonality or no correlation.

- **Ranking and Recommendation:** Once the similarity scores are computed, the system ranks the items based on these scores. Items with higher similarity scores to the user's profile are given higher ranks and are recommended to the user. The top-ranked items are typically presented as recommendations.

Figure 2 explains the implementation of the Content-Based Filtering algorithm based on user behavior when visiting a product. The visit data is stored in a table called "hit_log". The results of each product visit are then processed using a REST API presented in JSON format with the title "usersHit", consisting of two columns: the "name" column as the product name and the "total" column representing the total number of user visits to that product. Next, each word in the product name obtained from "usersHit" is presented through a column titled "keyword".

Subsequently, a product data search is conducted based on the products generated through "usersHit" data and the product names generated through "keyword" data, named "similar". The output from the "similar" dataset consists of recommended products based on products frequently visited by users, including columns for ID, SKU, line sheet, name, price, and images from the product data. The results from the "similar" dataset are displayed on the user's product detail page.

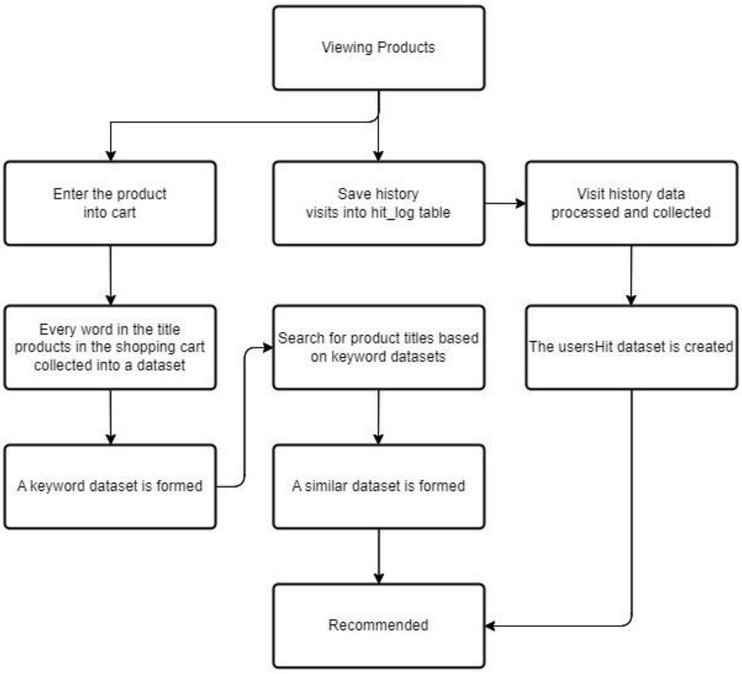


Figure 2. Implementation of content based filtering to aleza online store

2.3. Apriori Algorithm

The next step is to implement the Apriori algorithm. The Apriori algorithm is a popular data mining technique used in e-commerce and retail for market basket analysis. Market basket analysis is the process of discovering associations or relationships between products that are frequently purchased together by customers. The advantage of this algorithm is that it can give understanding to make decisions related to product placement, cross-selling, and targeted marketing. The implementation steps of the Apriori algorithm in the study are explained below.

- **Data Collection**: data used in this study contains 2,738 data of products which contains information regarding Linesheet, Stock Keeping Unit (SKU), Product name, Size, and Price. The next data used is data of transactions. 324 of data which contains information about Invoice, Linesheet, SKU, Quantity, and Price is used.
- **Data Pre-processing**: The dataset is then processed through a database for systematic processing. The processing process within the database involves importing data from the dataset into MySQL using Navicat software, and then grouping the data through Structured Query Language (SQL) queries.
- ***Itemset* Generation**: Next, the Apriori algorithm is applied to the homepage, product detail page, shopping cart page, and admin page through JSON for one or more *itemsets* with a combination of *itemsets* to find Support, Frequency, and Confidence values in Association Rules as shown in Equation 2 until Equation 4.

$$Support(X) = \frac{Number\ of\ Transactions\ contains\ X}{Total\ number\ of\ transactions} \quad (2)$$

$$Frequency\ (X) = Count\ of\ occurence\ (X) \quad (3)$$

$$Confidence(A \rightarrow B) = \frac{Support(A \cup B)}{Support\ (A)} \quad (4)$$

where $A \cup B$ represents the joint occurrence of items A and B. Support $(A \cup B)$ the support of the combined *itemset* $A \cup B$. $Support(A)$ is the support of the antecedent *itemset* A.

- **Candidate generation**: If the output value of the Association Rules exceeds 1, then the generated item combinations are predicted to be purchased in the next transaction.
- **Pruning**: Pruning is an important step in the Apriori algorithm to reduce computational complexity. Candidate *itemsets* that contain subsets that are not frequent are eliminated. This reduces the number of candidates *itemsets* that need to be considered for the next iteration.
- **Support calculation**: After pruning, the algorithm calculates the support of the remaining candidate itemsets. Only *itemsets* that meet the minimum support threshold are retained as frequent *itemsets*. In this study, the threshold value used is 1 as mentioned in the step for Candidate Generation.
- **Association Rule Generation**: Once the frequent *itemsets* have been identified, association rules are generated from them. Association rules consist of an antecedent (the itemset on the left-hand side) and a consequent (the item on the right-hand side).
- **Rule Evaluation**: The evaluation is based on metrics which are confidence and lift. Confidence measures the likelihood that the consequent will be purchased given the antecedent, while lift measures the strength of the association between the items in the rule.

Figure 3 explains the steps in implementing the Apriori algorithm.

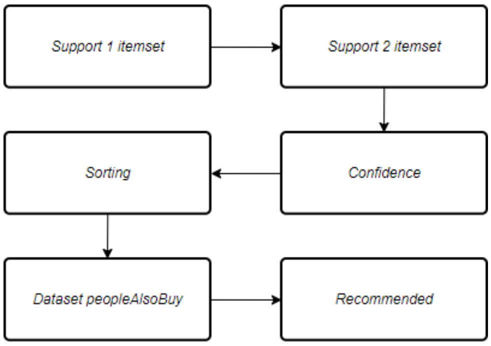


Figure 3. Flowchart of Apriori algorithm

The next step is to sort based on the highest confidence value. The output from the "peopleAlsoBuy" dataset is displayed on the user's shopping cart page and the admin's transaction page. The dataset, which has been encapsulated in a REST API using JSON, is then presented within the application.

2.4. Analysis Method

To measure the quality of a system, quality dimensions are required. In this case, the quality of the Recommendation System and the Smart Shopping System Aleza was assessed based on quality dimensions that encompass operational aspects, display aspects, speed aspects, interaction aspects, and benefit aspects. Measurement data is obtained through questionnaires administered to system users. The success of the recommendation system is marked by user satisfaction; however, satisfaction will not hold much meaning if the system does not lead to improved individual and organizational performance.

The type of data used in this research is primary data in the form of questionnaires containing respondents' perceptions with a Likert scale of 1-4, which includes very dissatisfied, dissatisfied, satisfied, and very satisfied. Data collection was carried out through a direct survey, where respondents were provided with questionnaire sheets and asked to fill them out. Subsequently, the completed questionnaires were collected.

The survey was conducted twice, before the implementation of the proposed system and after the implementation. Additionally, the questionnaires are divided internally (Aleza's staff) and for the customers. Next, the respondents were grouped into 4 different groups which are General Users, Management Users, Consumers, and Administrator users.

Table 1 shows the questionnaires given to the shop's staff, while **Table 2** is for the customers. The result was evaluated to show the need for an optimized and effective online shopping platform in Aleza.

Table 1. Questionnaire for Internal Staff

No.	Questions
1	To make the product sell quickly, there needs to be an online store platform that can be accessed by consumers
2	Discounted products are highly favored by consumers
3	Recommendation products need to be displayed to attract consumers to buy the offered products
4	Product categorization is needed to make it easier for consumers to find products according to their categories
5	Recommendation products can increase store sales

Table 2. Questionnaire for General Customers

No.	Questions
1	I usually buy products that have received good ratings from consumers
2	I like products that have discounts
3	I prefer online shopping over going to a physical store
4	Product categorization helps me find products according to their categories
5	I like products recommended by the store

The deployment of the proposed system is implemented on the hardware and software side. Hardware includes Intel Core i7 2.13 GHz, 8 GB RAM, 256 GB SSD, 2

GB VGA and printer. For the software, Windows 10 Pro OS, Xampp, Php, phpMyAdmin, Visual Code, Laravel, and Postman are used.

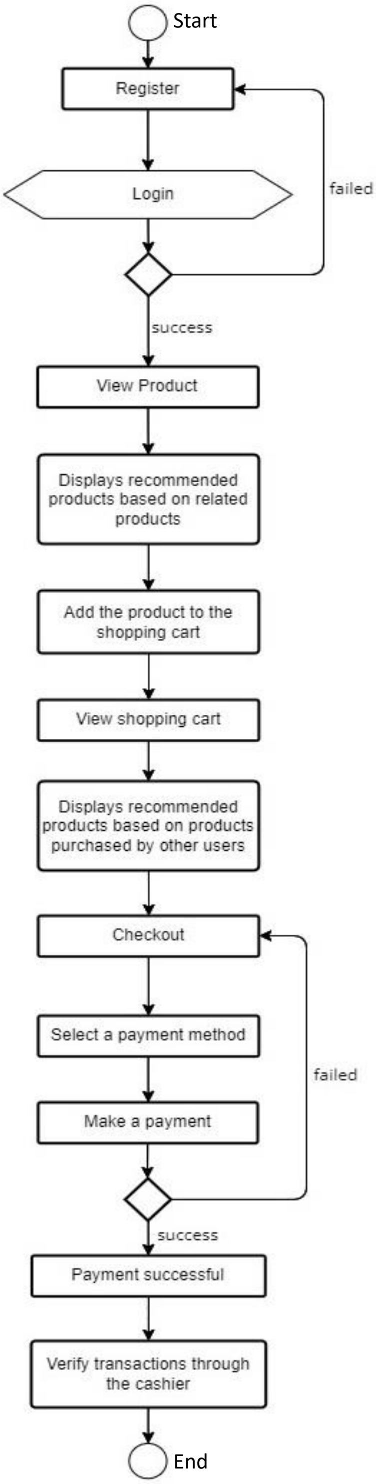


Figure 4. Flowchart of user interface

Figure 4 shows the flowchart of the user interface that is proposed in this study. The user interface includes a login page, list of products, recommended products page, shopping cart, payment method page, and verification page. The user interface is designed based on the Use case diagram as shown in **Figure 5**.

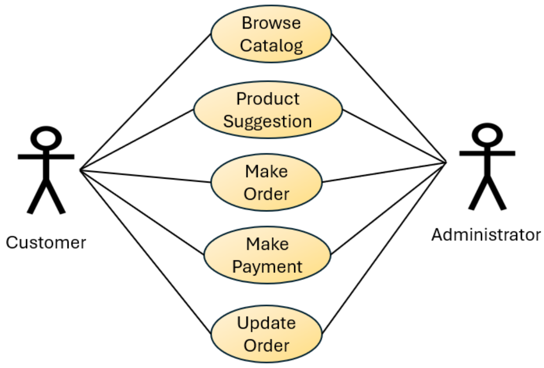


Figure 5. The use case diagram for the smart shopping system

3. RESULTS AND DISCUSSION

This section presented the results obtained from the study. The results were divided into four parts, which are the data selection and pre-processing, implementation of Content-based filtering, implementation of the Apriori algorithm, and the evaluation of the proposed system.

3.1. Data Selection

Table 3 and **Table 4** show the sample data of the product and transaction data used in this study, respectively. As mentioned in Section 2.1, 2,738 product data and 324 transaction data are used in the study.

3.2. Data Preprocessing

This stage involves grouping product arrangements based on transactions that have been made. The data is processed into the database for automatic processing by the system, using previously created transaction data. The transaction dataset is then processed and imported into the database. There are 2 tables in the transaction, namely the transaction as shown in

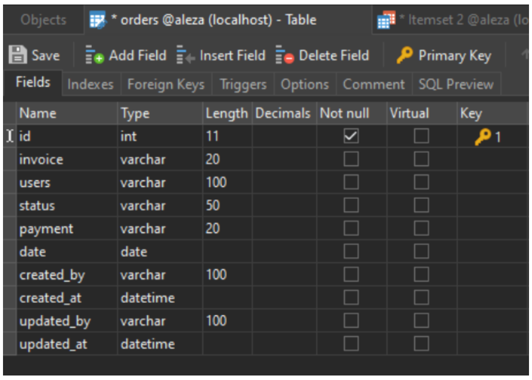
Figure 6, and the *detail_transaction* table as in **Figure 7**.

Table 3. Data of Products

No	Line-sheet	SKU	Names	Size	Price (Rp. k)
1	SO111/01047	AB-A2104-F-C	Mevina Top Crème	F	295
2	SO111/00167/01047	AB-A1902-F-S	Salza Top Sand	F	285
3	SO111	AB-B4603-S-B	Sean Pants Polka Brown	S	275
4	SO111/01047	AB-B4603-M-B	Sean Pants Polka Brown	M	275
5	SO111/01047	AB-B4603-L-B	Sean Pants Polka Brown	L	275

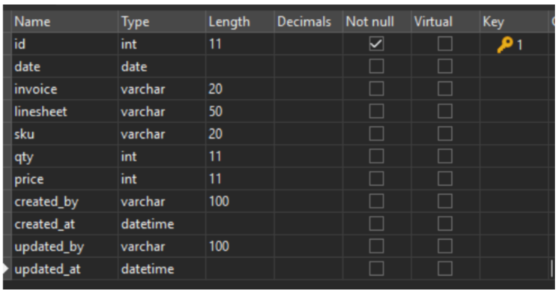
Table 4. Data of Transactions

Date	In-voice	SKU	Prod-uct	Qty	Price (Rp. k)
01-Dec-22	ACH-29094	ALBETOBLLO-OG	Bexy Tunic Dusty Blue (L)	1	475
01-Dec-22	ACH-29095	ALMITOORXL-XQ	Mirza Top Light Orange (XL)	1	475
01-Dec-22	ACH-29096	ALBIDRBLSO-ZR	Billa Dress Navy (S)	1	795
01-Dec-22	ACH-29097	ALBETOBLLO-OG	Bexy Tunic Dusty Blue (L)	1	475
01-Dec-22	ACH-29098	ALBATOBLSO-DB	Bexy Tunic Dusty Blue (S)	1	355



Name	Type	Length	Decimals	Not null	Virtual	Key
id	int	11		☑	☐	1
invoice	varchar	20		☐	☐	
users	varchar	100		☐	☐	
status	varchar	50		☐	☐	
payment	varchar	20		☐	☐	
date	date			☐	☐	
created_by	varchar	100		☐	☐	
created_at	datetime			☐	☐	
updated_by	varchar	100		☐	☐	
updated_at	datetime			☐	☐	

Figure 6. The structure of the transaction table



Name	Type	Length	Decimals	Not null	Virtual	Key
id	int	11		☑	☐	1
date	date			☐	☐	
invoice	varchar	20		☐	☐	
linesheet	varchar	50		☐	☐	
sku	varchar	20		☐	☐	
qty	int	11		☐	☐	
price	int	11		☐	☐	
created_by	varchar	100		☐	☐	
created_at	datetime			☐	☐	
updated_by	varchar	100		☐	☐	
updated_at	datetime			☐	☐	

Figure 7. The structure of the detailed transaction table

The transaction table stores transaction data such as invoice number, transaction date, and total transaction, while the *detail_transaction* table stores product data purchased such as product SKU number and product quantity based on the invoice number in the transaction table.

3.3. Combination of Content-Based Filtering and Apriori Algorithm

Table 5 represents some of the transactions for one itemset from the processed transaction data. The *Support* value is obtained by using Equation 2.

Table 5. The Support Value for The Combination of 1 Itemset

No.	Item	Total	Support (%)
1	Voxy Shirt Black	59	24.38
2	Viran Shirt Blue	15	6.20
3	Vie Shirt Mix	15	6.20
4	Viqa Shirt Purple	14	5.79
5	Virly Shirt Blue	8	3.31

Table 6 represents some of the results for the combination of two itemset. In this case, the *Support* value is obtained by using Equation (5).

$$Support\ (P \cap Q) = \frac{\sum Trasnsaction\ containing\ P\ \&\ Q}{\sum Transaction} \qquad (5)$$

From **Table 6**, it is seen that eight transactions were found that meet the association rules, which were used as recommendation products, consisting of 7 datasets based on confidence values and 1 dataset based on support values as highlighted in **bold** in the table. This result shows the ability of Content-based filtering to give recommendations related to the user's preferences.

Once the calculation has been completed by the Content-Based filtering, the next step was the implementation of Apriori algorithm in the case study. **Figure 8** shows the implementation result of the proposed method. It is seen that the Apriori algorithm can suggest products that are related to the products that have been ordered by customers.

3.4. Evaluation of Proposed System

The evaluation was conducted using a questionnaire as explained in Section 2.4. The results are shown in **Figure 9** and **Figure 10**.

Figure 9 shows the results from internal respondents. From the 5 questions given in the questionnaire and by considering the value of *strongly agree*, question #3, "*Recommendation products need to be displayed to attract consumers to buy the offered products*", has the highest result where 67% of respondents strongly agree with the question. This shows that recommendation systems in an online shop are important.

Question #4, "*Product categorization is needed to make it easier for consumers to find products according to their categories*" has result in only 13% strongly agree, where 87% of respondents answer agree. This result shows that all the respondents agree that product categorization is important. This is true since most of the customers are trying to save their time in finding the appropriate products.

Figure 10 shows the result of the questionnaire with the General Customers as the respondents. Based on the figure, question #2 and #5 have 30% of "strongly agree" result. It shows that general customers prefer there should be a recommendation system for online shopping and discounts. Each evidence shows the characteristics of general customers who want an easiness in online shopping experience.

Table 6. The support value for the combination of 2 itemset

No.	Product	Item p	Total	Support (%)	Confidence (%)
1	Voxy Shirt Black, Nafra Dress Mix	59	3	1.24	5
2	Viran Shirt Blue, Viera Printed Inner Mix	26	2	0.83	13
3	**Nadra Tunic Black, Meiva Tunic Mix**	**2**	**2**	**0.83**	**100**
4	Hailey Pleated Shirt Off white, Helga Knit Sweater Navy	1	1	0.41	**100**
5	Samira Bergo Teal Green, Samira Bergo Light Gray	3	1	0.41	33
6	Brena Organza Tunic Set Off White, Celya Tunic Black	2	1	0.41	50
7	Sahara Plain Scarves Copen Blue, Sahara Plain Scarves Saddle Brown	2	1	0.41	50
8	Veline Pleats Skirt Black, Viera Printed Inner Pink	3	1	0.41	33
9	**Hyena Shirt Olive Green, Hyera Pants Olive Green**	**1**	**1**	**0.41**	**100**
10	Exa Denim Black, Naisya Top Black	3	1	0.41	33
11	**Vian Pants Navy, Noha Pants Black**	**1**	**1**	**0.41**	**100**
12	**Cenna Shirt Black, Hanna Shirt Offwhite**	**1**	**1**	**0.41**	**100**
13	**Camira Tunic Off White, Mazira Tunic Mix**	**1**	**1**	**0.41**	**100**
14	**Gill's Shirt is Light Gray, and Della's Shirt Emerald**	**1**	**1**	**0.41**	**100**
15	Mandy Shirt Dress Dusty Blue, Masya Shirt Dusty Blue	4	1	0.41	25

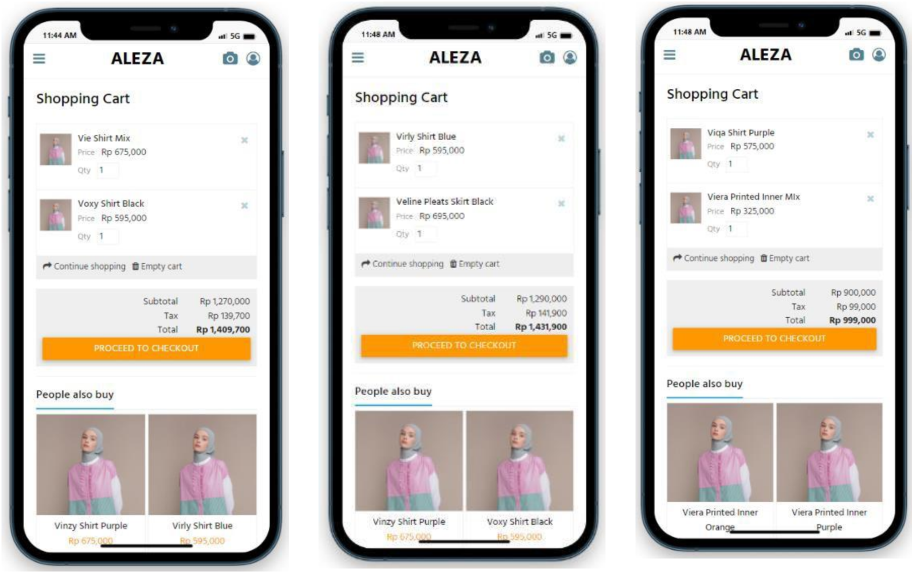


Figure 8. Content-based filtering and Apriori implementation

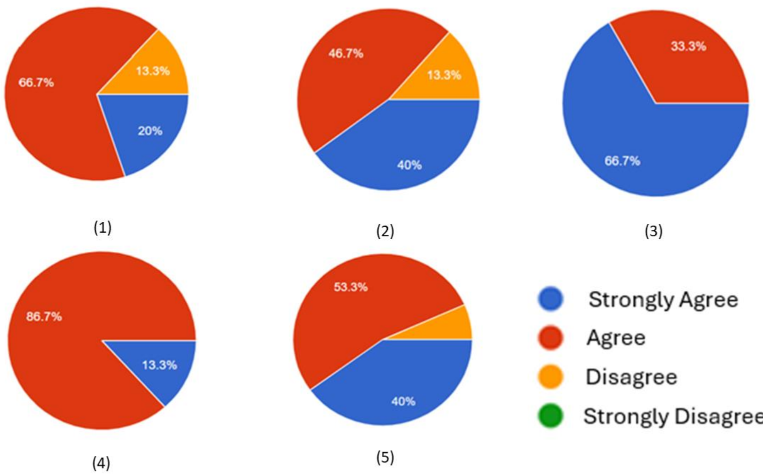


Figure 9. Internal respondant's answer based on the questionnaire in Table 1

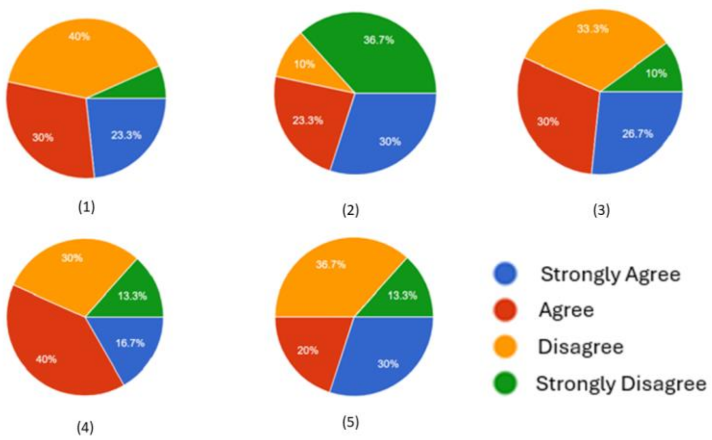


Figure 10. General customer's answer based on questionnaire in Table 2

4. CONCLUSION

The paper addresses the challenges of modern online shopping by proposing innovative solutions that integrate Recommendation Systems and the Smart Shopping System. It discusses the motivation behind the study, emphasizing the need for improved online shopping experiences. The study focuses on Aleza, a fashion retailer, as the object of research aiming to enhance its online platform. The study proposed Content-Based Filtering and the Apriori algorithm to optimize online shopping and improve user satisfaction.

The research successfully implements and evaluates a Recommendation System and a Smart Shopping System for Aleza. By leveraging Content-Based Filtering and the Apriori algorithm, the study demonstrates the ability to provide personalized product recommendations and facilitate efficient product searches. The result shows almost 98% confidence level for the combination of products. Additionally, the evaluation results indicate positive feedback from both internal staff about 95% and customers about 60%, highlighting the importance of recommendation systems and improved online shopping experiences.

Future research direction could explore further enhancements to the Recommendation System and the Smart Shopping System, incorporating advanced machine learning techniques such as deep learning models. Additionally, conducting longitudinal studies to assess the long-term impact of these systems on user engagement and business performance would provide valuable insights. Moreover, expanding the application of these systems to other retail sectors and exploring integration with emerging technologies like augmented reality could open up new avenues for enhancing the online shopping experience.

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