Jurnal Mandiri IT
Vol. 14 No. 1, July(2025), pp. 231-244

ISSN 2301-8984 (Print), 2809-1884 (Online)
Published by Institute of Computer Science

# Implementation of association method using fp-growth algorithm on sales transaction data at Koperasi Primer Pullahta Hankam Pusdatin KEMHAN RI

**Regifia Ningrum Nur Aulia[1], M Azhar Prabukusumo [2], Ajeng Hidayati[3]**
[1,2,3] Faculty of Defense Engineering and Technology, Informatics, Universitas Pertahanan Republik Indonesia, Bogor, Indonesia

**ARTICLE INFO**

***Article history:***

Received Jun 30, 2025
Revised Jul 16, 2025
Accepted Jul 28, 2025

***Keywords:***

Association Rules;
Data Mining,
FP-Growth Algorithm;
Lift Ratio;
Sales Transaction.

**ABSTRACT**

The conventional recording of sales transaction data frequently results in inaccuracies and presents significant obstacles to comprehensive data analysis. This study was conducted at Primkop Pullahta Hankam Pusdatin Kemhan RI with the aim of generating a product list based on item categories that are most frequently purchased together. These item combinations are expected to assist the cooperative in optimizing sales performance. The research employed a data mining technique known as association rule mining, which is designed to identify and predict customer purchasing behavior through analysis of transaction patterns. The dataset used comprised sales transaction records collected between September and November 2024. The FP-Growth algorithm was selected for its efficiency in identifying frequent itemsets without candidate generation. This algorithm utilized minimum support and confidence thresholds to generate association rules. The modeling process produced five association rules, each meeting the criteria of a minimum support of 20% and a minimum confidence of 80%, indicating strong co-occurrence among specific product combinations. Functional testing using the blackbox method demonstrated that all implemented features performed in accordance with specified functional requirements. The findings offer valuable insights for cooperative management by enabling data-driven decision-making in inventory planning, promotional bundling, and strategic sales targeting. These implications underscore the practical contribution of the research in enhancing operational efficiency and sales strategy within the cooperative sector.



***Corresponding Author:***

Regifia Ningrum Nur Aulia,
Informatics,
Universitas Pertahanan Republik Indonesia,
Kawasan IPSC Sentul, Sukahati, Kec. Citeureup, Kabupaten Bogor, Jawa Barat, 16810. Indonesia.
Email: regifianingrum@gmail.com

## 1. INTRODUCTION

A cooperative is an organization whose membership is based on the principles of collaboration and kinship, aimed at improving the welfare of its members (Arifandy et al., 2020). The Primary Cooperative for Defense and Security Data Collection and Processing (Primkop Pullahta Hankam) plays a vital role in supporting the needs of the members of the Data and Information Center of the Ministry of Defense of the Republic of Indonesia (Pusdatin Kemhan RI). These needs highlight the importance of a system capable of managing data in a structured and efficient manner through the support of information technology. As it evolves, information technology has the potential to enhance cooperatives' capabilities in recording and managing data (Septiandito Saputra, 2021).

Primkop faces several operational challenges that can impact its business activities. Based on an interview conducted with the head of the cooperative store on November 18, 2024, several issues were identified within Primkop Pullahta Hankam Pusdatin Kemhan RI. The primary problem lies in the conventional method of recording sales transactions. Currently, sales are first noted manually on paper by the storekeeper and later transferred into Excel spreadsheets at the end of the day. This manual process is time-consuming and prone to recording errors. Moreover, the recorded transaction data has not been fully utilized to support decision-making processes. As a result, analyzing sales transaction data becomes difficult and inefficient. In response to these challenges, Primkop Pullahta Hankam Pusdatin Kemhan RI requires a more modern approach to transaction recording one that integrates data analysis capabilities to assist the store manager in making informed decisions to optimize sales performance.

In developing this research, the authors have referred to several previous studies to support the analysis of the issues faced by Primkop. A study conducted by (T. Handayani et al. 2024) analyzed purchasing patterns at Toko Sahabat Collection and identified 32 association rules using the FP-Growth algorithm. Furthermore, a study by (Anggrawan et al. 2021) on purchasing patterns at an accessory store in West Nusa Tenggara demonstrated that comparative analysis of algorithms can improve product placement management and enhance decision-making strategies based on identified purchasing trends. In addition,(Mariko et al. 2021) found that analyzing purchasing patterns of interrelated products using the FP-Growth algorithm resulted in faster identification of suitable products for targeted promotions to customers. Furthermore, the study conducted by (Purba & Firdaus, 2021) produced data analysis results using support and confidence parameters, which were subsequently implemented into a system. In a related study, (Djabalul Lael & Pramudito, 2023) demonstrated that the FP-Growth algorithm is effective in identifying significant consumer purchasing patterns within motorcycle spare parts sales transaction data. Similarly, (Wandri & Hanafiah, 2022) showed that the application of the FP-Growth algorithm to sales transaction data can assist in designing more effective marketing strategies based on purchasing behavior analysis of IT products. Lastly, the study by (Yanti et al., 2024) generated five association rules used to optimize product layout, shopping catalogs, and promotional strategies—such as discount vouchers—in order to enhance customer purchasing patterns and increase store revenue.

This study aims to develop a web-based transaction recording system that can present the outcomes of association rule analysis using the FP-Growth algorithm, and to examine sales transaction patterns by applying the FP-Growth algorithm at Primkop Pullahta Hankam Pusdatin Kemhan RI. This research is expected to provide both practical and theoretical benefits. Practically, it aims to reduce errors in transaction recording by developing a web-based sales recording system for Primkop Pullahta Hankam Pusdatin Kemhan RI. Furthermore, analyzing sales transaction patterns through the FP-Growth algorithm is anticipated to contribute to optimizing sales and improving the operational effectiveness of the cooperative. From a theoretical perspective, this research is expected to provide a reference for the development of comparable systems aimed at enhancing cooperative performance. This study is also expected to make a meaningful contribution to the development of association rule mining methodologies, with a particular focus on the FP-Growth algorithm, while simultaneously offering deeper insights into the structure and dynamics of transactional patterns within cooperative organizations.

Although previous studies have proven the effectiveness of the FP-Growth algorithm in analyzing purchasing patterns in the retail and commercial store sectors, there is still a gap in research on its application in the context of government cooperatives, particularly those operating within bureaucratic structures such as Primkop Pullahta Hankam Pusdatin Kemhan RI. Government cooperatives have their own unique organizational characteristics, such as administrative regulations, hierarchical structures, and limitations in the adoption of information technology. Therefore, the scientific urgency of this research lies in testing the effectiveness of the FP-Growth algorithm in an environment with dynamics that differ from those of the commercial sector. This research not only contributes practically to improving the operational efficiency of cooperatives but also expands the scope of data mining utilization in the context of government institutions. Thus, this research aims to fill the scientific gap in the literature regarding the application of association rule mining in state-owned non-profit institutions, as well as enriching understanding of how this algorithm can be adapted to improve the quality of data-driven decision-making in the public sector.

## 2. RESEARCH METHOD

### Research Design

The research design refers to the plan or strategy employed by the researcher to answer the research questions and systematically achieve the stated objectives. It represents the chosen approach to guide the research process, encompassing the application of various methods. The overall research design is presented in Figure 1.

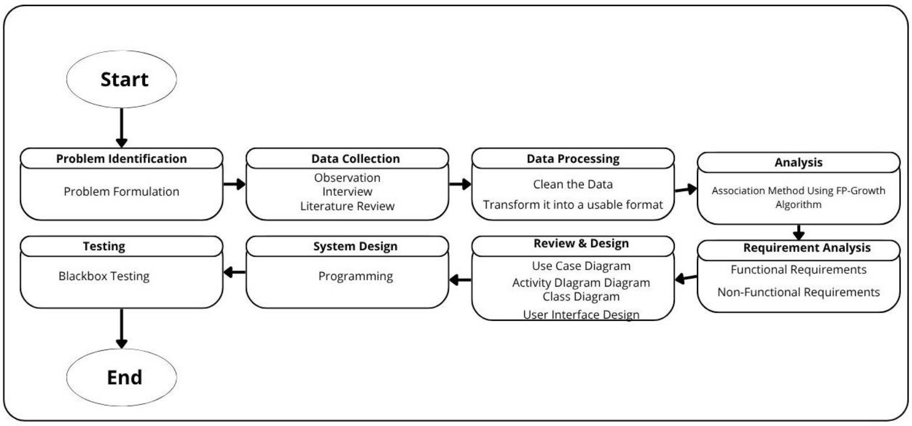


Figure 1. Reseach Design

Figure 1 illustrates the systematic flow of stages carried out in this research. The first stage is problem identification, which involves determining the research focus and objectives by understanding the sales transaction processes at Primkop Pullahta Hankam Pusdatin Kemhan RI. This is followed by data collection through observation, interviews, and literature review, during which sales transaction data are gathered in both hardcopy and softcopy formats. The collected data then undergo data processing, which includes selection, preprocessing, and transformation to prepare the data for analysis. In the analysis stage, the FP-Growth algorithm is applied to identify association patterns among product categories, and evaluation is performed using the lift ratio method. Subsequently, a requirement analysis is conducted to identify both functional and non-functional system requirements. The next phase is review and design, where the system is visually designed using diagrams and mockups. Finally, in the testing stage, black-box testing is conducted to evaluate the system's functionality.

### Data Mining

According to (Etiowo & Okoronkwo. 2023), their study states that data mining using various algorithms and methods is utilized to process large-scale data into meaningful and useful outputs. The commonly used data mining methods are explained as follows.

**a. Classification**

In the study conducted by (De Wibowo Muhammad Sidik et al. 2020), it is stated that In the context of data mining, classification entails the systematic exploration of vast data collections to uncover latent structures and predictive patterns within the data, assisted by machine learning techniques capable of handling unstructured data outputs. The classification process aims to map target variables into specific categories. Commonly used classification methods include C4.5, Bayesian networks, K-Nearest Neighbor (KNN), genetic algorithms, and rule-based approaches such as "if-then" rules.

**b. Clustering**

Clustering is a process in data mining that groups objects based on similarities, resulting in the formation of clusters containing similar characteristics (Hakim et al., 2023) Each cluster consists of data points that exhibit high similarity within the group but are significantly different from those in other groups. According to a study by (Rahayu et al. 2024) in the field of education, clustering using the K-Means algorithm serves as a valuable tool for analyzing educational data, as it can uncover patterns within large datasets—such as mapping high-achieving students.

**c. Association**

The association method in data mining is used to identify attributes that frequently occur together within a specified time frame (Octaviani & Dewi 2020). In a study conducted by (Wijaya et al. 2020) it is stated that the FP-Growth algorithm is part of the association approach used to detect frequent item patterns within large datasets. The FP-Growth algorithm is an enhancement of the Apriori algorithm, addressing its limitations—particularly in terms of data processing efficiency. In a business context, the association method is commonly referred to as Market Basket Analysis (MBA), which involves identifying items that are frequently purchased together as recorded in sales transactionsThe method utilizes two fundamental indicators: *support*, representing the proportion of transactions that contain a particular itemset, and *confidence*, reflecting the likelihood that one item appears given the presence of another within the same transaction.

**Knowledge Discovery in Database (KDD)**

According to (Lintang & Lestari 2023), Knowledge Discovery in Databases (KDD) is a process used to extract meaningful information and patterns from data stored in a structured database system. The design flow of the KDD process in data mining is presented in Figure 2 below.

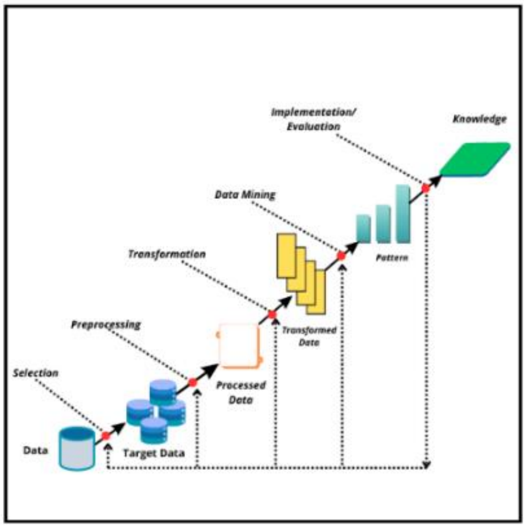


Figure 2. KDD Design in Data Mining

The main steps in the Knowledge Discovery in Databases (KDD) process, as illustrated in Figure 2, consist of the following stages.

a. Selection, This is the initial stage of the KDD process. It involves selecting relevant data from available sources to exclude irrelevant or unnecessary data that does not align with the analysis objectives.
b. Preprocessing, This phase focuses on improving data quality by addressing errors and irregularities, such as removing redundant entries, imputing or excluding missing values, and harmonizing diverse data formats to ensure consistency.
c. Transformation, After preprocessing, the data undergoes transformation to convert it into a format that is more suitable for analysis. This step includes data normalization and variable encoding to ensure compatibility with analytical algorithms.
d. Data Mining, This is the core stage of the KDD process where analytical methods are applied. It involves the use of algorithms to identify patterns and relationships within the data. In this study, the association method is employed, specifically using the FP-Growth algorithm to discover frequent itemset patterns.
e. Knowledge, The final stage is the extraction of knowledge, which refers to the meaningful patterns or insights obtained from the data mining process. These patterns can be interpreted and applied to support decision-making according to the specific needs of the organization.

**Association Methods**

According to (P. K. Handayani & Susanti 2019) association is a data mining method used to determine combination rules among items within discovered patterns from a dataset, thereby supporting upper-level management in the decision-making process. The association method is utilized to reveal relationships between items that tend to appear together in sales transactions (Anggrawan et al., 2021). The association method employs two primary metrics in its analysis: support, which serves as an indicator to measure how influential or frequent an item is within the system, and confidence, which is used to assess the strength of the relationship between items in specified transactions This method, commonly known as Market Basket Analysis (MBA), is an approach used to analyze consumer purchasing behavior. It utilizes association rules to identify correlations between items, with the FP-Growth algorithm playing a key role in discovering combinations of items frequently purchased together. The algorithm operates based on predefined thresholds of minimum support and minimum confidence, ensuring that only the most relevant and meaningful patterns are identified. (Herdyansyah et al., 2020).

**FP-Growth Algorithm**

FP-Growth is one of the algorithms applied in data mining methods to identify frequent co-occurring patterns within sales transaction data. It utilizes the association rule mining approach to uncover relationships between items within transactions (Firmansyah & Nurdiawan, 2023). According to (Supriyadi et al. 2020) the FP-Growth algorithm begins by determining a minimum support threshold, followed by the identification of frequent itemsets—known as the header table—and the construction of a frequent pattern tree (FP-tree) to efficiently represent and analyze the dataset. The flow diagram of the FP-Growth algorithm is presented in Figure 3 below.

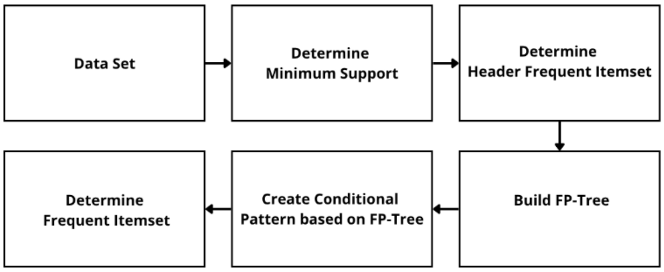


Figure 3. Flow Diagram of the FP-Growth Algorithm

**Lift Ratio**

The study conducted by (Takdirillah 2020) states that within association rules, lift ratio serves as a metric to determine the strength of the relationship between items in a given rule. Lift ratio is commonly used to evaluate whether an association rule is considered valid, as also emphasized by (Ashari et al., 2022). Lift ratio operates by comparing the confidence level of an association rule to a benchmark confidence value. The first step in calculating the lift ratio is to determine the confidence of the rule namely, the probability that item A appears in a transaction that also contains item B. Next, The benchmark confidence is determined by calculating the ratio of transactions that include item A to the overall number of transactions. Subsequently, the lift value is derived by dividing the obtained confidence by this benchmark confidence.

**Design System**

The use case diagram plays a role in visualizing the interactions between actors and the system functions they can access, based on their respective access rights. The activity diagram illustrates the flow of activities within a business process, while the class diagram is used to represent the relationships among class elements within the system design(Setiaji et al., 2024). Use Case Diagram presented in Figure 4 below.

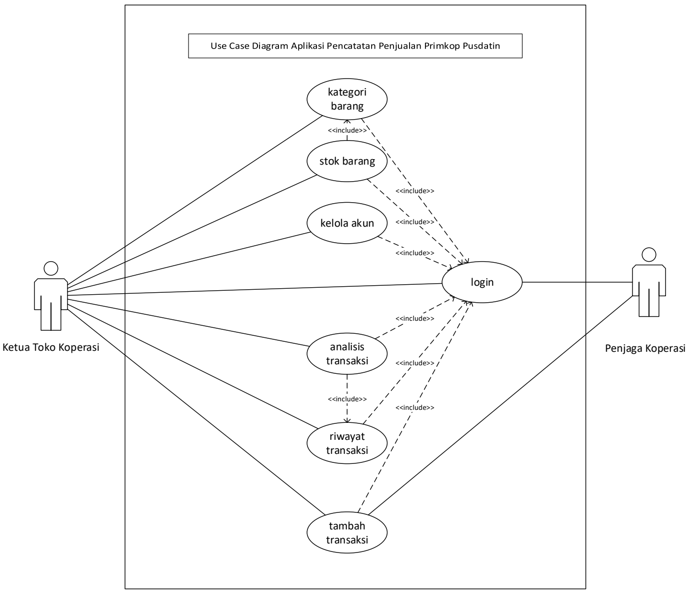


Figure 4. Use Case Diagram

As illustrated in Figure 4, the cooperative store manager holds system authority, including the ability to manage products, which covers both category and inventory management within Primkop. The store manager also acts as a superadmin, with the authority to manage user accounts. Additionally, the store manager can perform transaction analysis by applying the association method using the FP-Growth algorithm. The manager also has access to view transaction history, which contains records of sales transactions, and can add new sales transactions. Meanwhile, the cooperative staff member has limited access rights, specifically the ability to add sales transactions. All transactions entered by the cooperative staff are automatically stored in the transaction history.

In addition to the use case diagram, a class diagram is utilized to complement the understanding of the system design. The class diagram provides a clear representation of the system's structure and the relationships between classes, serving as a blueprint that outlines the key components, attributes, methods, and associations within the system. This diagram is essential for modeling the static aspects of the system and facilitating effective system development and implementation. Class Diagram presented in Figure 5 below.

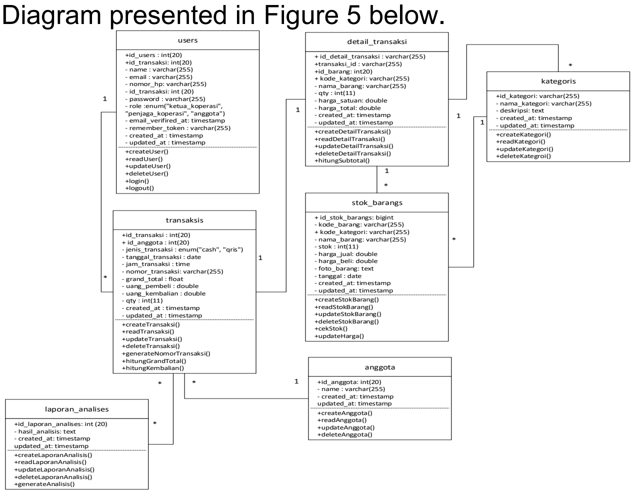


Figure 5. Class Diagram

Figure 5 presents the class diagram design used in this study. The class diagram illustrates the structure of the database within the system, which consists of seven main tables. For data analysis purposes, there is a report analysis table that stores the results of processed transaction data. Additionally, the transaction detail table functions to provide detailed information for each individual transaction. Notation in an activity diagram is used to model the workflow or processes within a system.

.

**Userinterface Design**

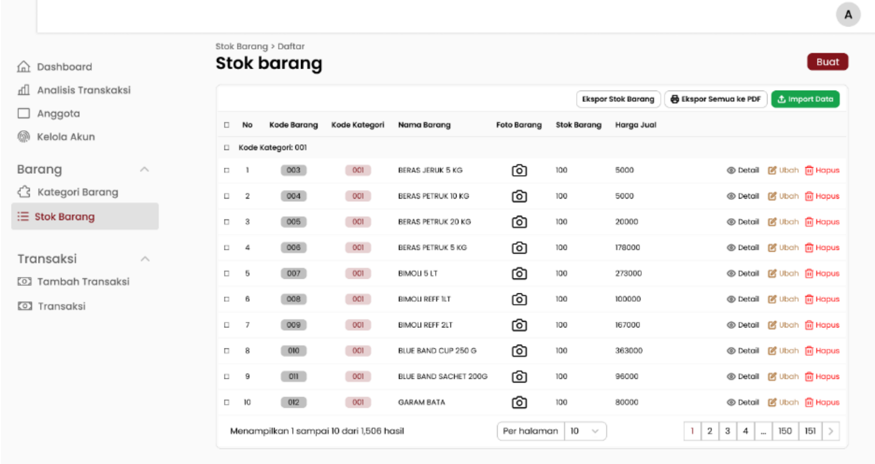


Figure 6. Userinterface Design Of Kelola Stok Barang

Based on Figure 9, the design of the inventory management interface allows the cooperative store manager to manage the inventory. On this page, the store manager can add new item data, import data from external files, or input data manually through the “Create” button form. In addition, the store manager can also view detailed item information, modify existing data, and delete unnecessary items. All features are designed to support the item management process by the store manager.

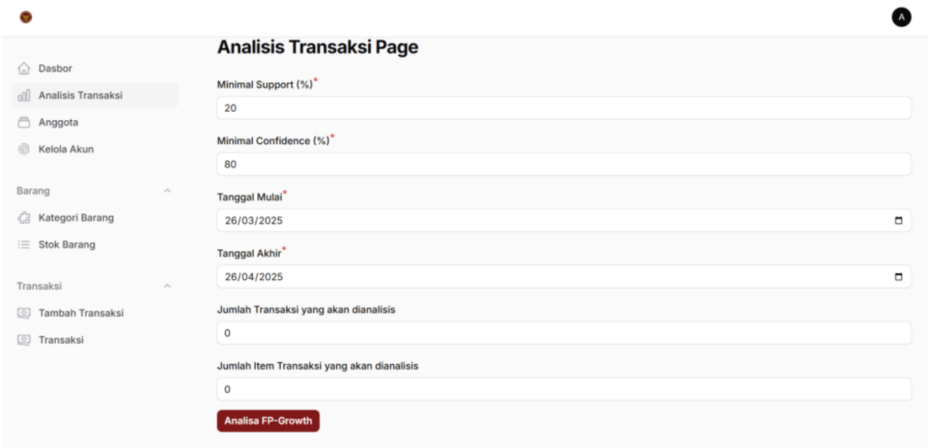


Figure 7. Userinterface Design Of Analisis Transaksi

Based on Figure 10, the design of the transaction analysis interface for the cooperative store manager illustrates that the analysis process begins by entering the minimum support and minimum confidence values as the fundamental parameters of the algorithm. Subsequently, the user selects the analysis period by specifying the start and end dates. The analysis process can then be executed using the “FP-Growth Analysis” button, which applies the FP-Growth algorithm based on the association method. The results of the transaction analysis are presented in a table containing information that can be utilized by the cooperative store manager. To strengthen the practical and academic contributions of this research, the association patterns discovered through the FP-Growth algorithm will be examined more deeply in terms of their business implications. Frequently co-purchased product combinations can be strategically utilized for promotional bundling, optimized product placement in the store layout, and the development of more targeted shopping catalogs. These patterns can also serve as a basis for customer loyalty programs, such as offering discounts or vouchers tailored to purchasing preferences. Furthermore, the findings of this study will be critically compared with previous research—such as those by Handayani et al. (2024) and Yanti et al. (2024)—to highlight the unique contribution of this study in the context of government cooperatives, which possess distinct characteristics compared to commercial retail businesses. This deeper analysis is expected to reinforce the originality and value of applying association rule mining techniques for strategic decision-making in public-sector cooperative organizations.

## 3. RESULTS AND DISCUSSIONS

This study aims to analyze purchasing patterns at the Pullahta Hankam Primary Cooperative, Pusdatin Kemhan RI, using the FP-Growth algorithm. The dataset analyzed consists of 6,258 transactions collected between September 2 and November 27, 2024, with a total of 27,650 items sold. Prior to analysis, the data underwent processing through the Knowledge Discovery in Databases (KDD) stages, including data selection, cleaning, and transformation, to ensure data quality. The analysis results were then implemented into a web-based application designed to assist the cooperative manager in identifying purchasing patterns and to support cooperative staff in managing transactions systematically.

Table 1. Primkop Sales Transaction Data

| Date | Transaction ID | Buyer | Type Code | Item Code | Item Name | Price |
|---|---|---|---|---|---|---|
| 02/09/2024 | TRX-20240902-1276 | HXXXX SXXXXXXXXX | 001 | 030 | CORNET B | 35000 |
| 02/09/2024 | TRX-20240902-1276 | HXXXX SXXXXXXXXX | 002 | 009 | ASTOR SINGLE | 1000 |
| 02/09/2024 | TRX-20240902-1276 | HXXXX SXXXXXXXXX | 004 | 036 | DOVE RAMBUT RUSAK 135 ML | 23000 |
| 02/09/2024 | TRX-20240902-1276 | HXXXX SXXXXXXXXX | 009 | 013 | BATERAI ENERGIZER A3 KUNING | 17000 |
| 02/09/2024 | TRX-20240902-1276 | HXXXX SXXXXXXXXX | 012 | 018 | JAHE WANGI ISI 25 | 25000 |
| 27/11/2024 | TRX-20241127-9983 | CXXX | 001 | 015 | BLUE BAND CUP 250 G | 22000 |
| 27/11/2024 | TRX-20241127-9983 | CXXX | 001 | 021 | BONCABE LEVEL 30 BOTOL | 10000 |

An example of the data, as shown in Table 1, includes sales transaction information from Primkop Pullahta Hankam Pusdatin Kemhan RI. This information comprises the transaction date, transaction ID, buyer's name, item type code, item code, item name, and the price of each item sold. This dataset will be utilized in the subsequent data processing stages through the Knowledge Discovery in Databases (KDD) methodology.

**Selection**

Data selection is the initial stage aimed at extracting relevant data from a large dataset prior to the preprocessing and further analysis phases. In this study, the selected data includes only the Transaction ID and Item Name, as presented in Table 2

Table 2. Selected Data

| Transaction ID | Nama Barang |
|---|---|
| TRX-20240902-1276 | CORNET B |
| TRX-20240902-1276 | ASTOR SINGLE |
| TRX-20240902-1276 | DOVE RAMBUT RUSAK 135 ML |
| TRX-20240902-1276 | BATERAI ENERGIZER A3 KUNING |
| TRX-20240902-1276 | JAHE WANGI ISI 25 |
| TRX-20240902-1285 | SUNSILK BLACK SHINE 70 ML |
| TRX-20241127-9983 | BLUE BAND CUP 250 G |
| TRX-20241127-9983 | BONCABE LEVEL 30 BOTOL |
| TRX-20241127-9983 | STELLA MATIC REFFIL LAVENDER |
| TRX-20241127-9983 | SMITH |
| TRX-20241127-9983 | CIMORY PASION FRUIT |

As shown in Table 2, the naming of the Transaction ID consists of three components: TRX, which denotes the transaction code; the date, indicating when the transaction occurred; and a unique number, representing the sequential order of the transaction. In addition, the item name refers to the products purchased by customers of Primkop Pullahta Hankam Pusdatin Kemhan RI.

**Data Preprocessing**

The next step is data preprocessing. In this stage, any transaction records that do not contain item names are removed. Additionally, item names are standardized to ensure consistency and prevent discrepancies in formatting that could result in the same item being recognized as different entries. Furthermore, the item names are classified into 10 distinct categories.

Table 3. Product Categories

| No. | Kategori |
|---|---|
| 1 | Bahan Pokok |
| 2 | Makanan Instan |
| 3 | Bumbu Penyedap |
| 4 | Minuman |
| 5 | Snack dan Camilan |
| 6 | Perlengkapan Rumah Tangga |
| 7 | Perawatan Diri |
| 8 | ATK |
| 9 | Rokok |
| 10 | Makanan Beku |

As shown in Table 3, the dataset is divided into 10 product categories, including staple foods, instant foods, seasonings, beverages, snacks and light meals, household supplies, personal care items, stationery (ATK), cigarettes, and frozen foods. Each category is assigned a category code to facilitate the construction of the FP-Tree during manual calculation. Grouping product names into these 10 categories aims to produce more accurate analysis results based on item categories. This approach is consistent with the study conducted by Gulo et al. (2023), who classified items into seven departments. After categorizing the products, each item name is replaced with its corresponding category label. This step allows the transaction data to be analyzed based on item categories rather than individual product names.

**Data Transformation**

At this stage, the data undergoes a transformation process to align with the modeling requirements, one of which involves converting categorical data into binary format. In binary transformation, each specific attribute value is converted into either a 0 or 1, where 0 represents a "false" condition (i.e., the item is not present) and 1 represents a "true" condition (i.e., the item is present). This transformation is essential to facilitate data processing, as most algorithms are designed to handle numerical data only.

Table 4. Data Transformation

| Transaction ID | BP | MA | BU | MI | SC | RT | PD | AT | RO | MB |
|---|---|---|---|---|---|---|---|---|---|---|
| TRX-20240902-1276 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| TRX-20240902-1285 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| TRX-20240902-1298 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| TRX-20240902-1369 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| TRX-20240902-1430 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| TRX-20240902-1730 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
| TRX-20240902-1765 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| TRX-20240902-1767 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| TRX-20240902-1771 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |

Based on Table 4, which presents the results of the transaction data transformation into binary tabular format based on ten item categories, each row represents a single transaction, while the columns represent the product categories. A value of "1" is assigned if a particular category appears in the transaction, and "0" if it does not. For example, although transaction TRX-20240902-1298 includes several items from the personal care category, only one "1" is recorded to indicate the presence of that category. After undergoing the processes of data selection, preprocessing, and transformation, a total of 6,354 transactions with 27,605 items were obtained, which are ready to be analyzed using the FP-Growth algorithm.

**System Implementation**

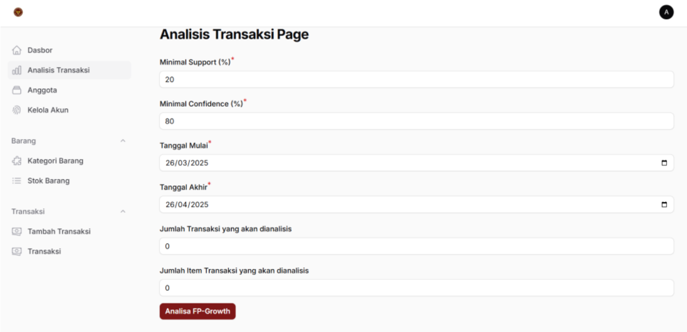

Figure 8. Page Display of Analisis Transaksi Page

In conducting transaction analysis, the head of the cooperative store inputs the minimum support and minimum confidence values through the system interface as shown in Figure 11 Subsequently, a transaction date range is selected to filter the transaction data according to the specified dates. Once the parameters are set, the system will display the number of transactions to be analyzed, as well as the number of items within those transactions. For the initial analysis, the transaction date range is filtered from 1 September 2024 to 30 September 2024. In the initial display, the head of the cooperative store enters the parameters, as illustrated in Figure 12 below.

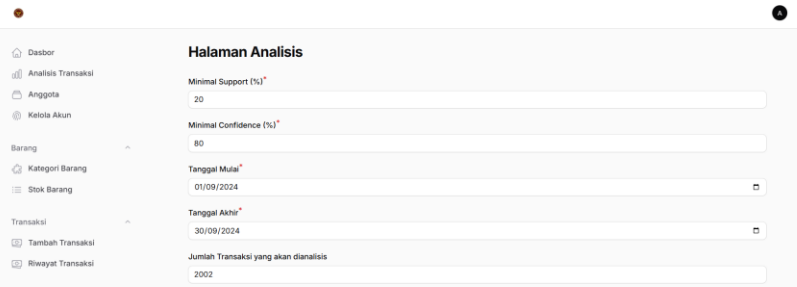

Figure 9. Chairman of the Cooperative Store inputs Parameters

Hasil Frequent Itemset (FP-Growth)

| No | Itemset | Support (%) |
|---|---|---|
| 1 | Minuman | 52% |
| 2 | Minuman - Snack dan Camilan | 24% |
| 3 | Minuman - ATK | 22% |
| 4 | Snack dan Camilan | 44% |
| 5 | Perlengkapan Rumah Tangga | 28% |
| 6 | Perawatan Diri | 81% |
| 7 | Perawatan Diri - Minuman | 43% |
| 8 | Perawatan Diri - Minuman - Snack dan Camilan | 20% |
| 9 | Perawatan Diri - Snack dan Camilan | 36% |
| 10 | Perawatan Diri - Perlengkapan Rumah Tangga | 23% |
| 11 | Perawatan Diri - ATK | 34% |
| 12 | ATK | 41% |

Figure 10. Frequent Itemset Transactioin Results

Figure 13 presents the results of the *frequent itemsets* obtained through the FP-Growth algorithm. It displays combinations of item categories that are frequently purchased together, along with their respective *support values* expressed as percentages. The personal care category has the highest support value at 81%, indicating that this category appears in the majority of transactions. It is followed by beverages at 52%, snacks & light meals at 44%, and stationery (ATK) at 41%. In addition, several item combinations show significant co-occurrence frequencies, such as personal care and beverages with a support of 43%, and personal care and snacks & light meals with 36%. After obtaining the frequent itemsets, the association rules can then be determined. The results of the association rules are presented in Figure 14 below

**Hasil Association Rules (FP-Growth)**

Aturan asosiasi berdasarkan kombinasi item yang sering muncul dalam transaksi.

| No | Jika beli ini | Maka beli ini | Support | Confidence | Lift |
|---|---|---|---|---|---|
| 1 | Minuman, Snack dan Camilan | Perawatan Diri | 20% | 85% | 1.05 |
| 2 | ATK | Perawatan Diri | 34% | 83% | 1.02 |
| 3 | Perlengkapan Rumah Tangga | Perawatan Diri | 23% | 83% | 1.02 |
| 4 | Snack dan Camilan | Perawatan Diri | 36% | 82% | 1.01 |
| 5 | Minuman | Perawatan Diri | 43% | 82% | 1.01 |

Figure 11. Association Rule Results

Based on Figure 14, which presents the results of transaction data analysis from September 1, 2024 to November 27, 2024, a total of five rules were generated that meet the minimum support and minimum confidence thresholds. These five rules are as follows: The association rule analysis revealed several significant purchasing patterns among customers at Primkop Pullahta Hankam Pusdatin Kemhan RI. Customers who purchased stationery (ATK) were likely to also buy personal care (Perawatan Diri) products, with a co-occurrence frequency of 34%, a confidence level of 83%, and a lift ratio of 1.02. Similarly, those who bought beverages (Minuman) tended to purchase personal care products as well, indicated by a co-occurrence frequency of 43%, confidence of 82%, and a lift ratio of 1.01. Household items (Perlengkapan Rumah Tangga) were also commonly purchased alongside personal care products, with a co-occurrence frequency of 23%, confidence of 83%, and a lift ratio of 1.02. In addition, customers who bought snacks (Snack dan Camilan) frequently also purchased personal care products, shown by a 36% co-occurrence frequency, 82% confidence, and a lift ratio of 1.01. Notably, when customers purchased both beverages and snacks together, the likelihood of also purchasing personal care products increased, with a support value of 20%, a higher confidence level of 85%, and a lift ratio of 1.05. These findings indicate strong cross-category purchasing behavior centered around personal care products, which can inform targeted promotional strategies and bundling initiatives.

**Blackbox Testing System Testing**

Blackbox testing is a method of application testing conducted without examining the internal structure of the system, focusing instead on functional testing based on input and output. This testing is applied to various features of the application, such as adding transactions, managing inventory, account management, transaction analysis, and the login system. The purpose of the testing is to ensure that each feature operates according to the functional requirements of Primkop Pullahta Hankam Pusdatin Kemhan RI. The testing results are based on the comparison between the given inputs and the outputs produced, aiming to detect any errors or inconsistencies within the system.

Table 5. Blackbox Testing

| No. | Testing Scenario | Expected Results | Test Results | Conclusion |
|---|---|---|---|---|
| 1. | The user enters their username and password after opening the login page. | By entering a username and password after opening the login page, the system ensures security and user access authorization. | As expected | Valid |
| 2. | Click “Create” in the category menu to add a new category by filling out the form provided. | With the “Create” feature in the category menu, users can easily add new categories for more structured data grouping. | As expected | Valid |
| 3. | Click “Edit” to edit existing data, then save the changes. | With the “Change” feature, users can edit existing data to ensure that information remains accurate and up to date. | As expected | Valid |
| 4. | Click “Export Inventory” to download the table data from the inventory page. | With the “Export Inventory” feature, users can download inventory data for documentation or further analysis. | As expected | Valid |

| | | | | |
|---|---|---|---|---|
| 5. | Click “Import Data” to add product data in accordance with applicable regulations. | With the “Import Data” feature, users can add large amounts of product data in accordance with the specified format. | As expected | Valid |
| 6. | Filter transaction history based on a specific date range. | The system displays a list of transactions corresponding to the selected date. | As expected | Valid |
| 7 | Click “Transaction Analysis” to start transaction analysis. | With the “Transaction Analysis” feature, users can identify transaction patterns to support business decision-making. | As expected | Valid |
| 8 | Click “Export Analysis Report” to download the transaction analysis results. | With the “Export Analysis Report” feature, users can download transaction analysis results for documentation and evaluation. | As expected | Valid |
| 9 | Click “FP-Growth Analysis” to perform transaction analysis using the FP-Growth algorithm. | With the “FP-Growth Analysis” feature, users can identify purchasing patterns based on the FP-Growth algorithm. | As expected | Valid |
| 10 | Click “Add Transaction Item” to add a new order. | With the “Add Transaction Item” feature, users can easily add new orders systematically and quickly. | As expected | Valid |

Based on the testing results using the Blackbox Testing method for the Cooperative Attendant role, as presented in Table 5, it can be concluded that all tested features functioned according to the defined functional requirements. Each scenario demonstrated that the system was able to respond to the inputs with the appropriate and expected outputs.

## 4. CONCLUSION

Based on the research conducted, it can be concluded that the web-based transaction recording system has been successfully designed and implemented to meet the operational needs of Primkop Pullahta Hankam Pusdatin Kemhan RI. The integration of the FP-Growth algorithm into the system has proven effective in identifying meaningful associations between product categories frequently purchased together. Analysis of transaction data from September 1, 2024, to November 27, 2024, resulted in five association rules, with the most prominent indicating that customers who purchase stationery (ATK) are also likely to purchase personal care products, supported by a confidence level of 83% and a lift ratio of 1.02. These findings have several practical implications. The identified purchasing patterns can be utilized to inform targeted marketing strategies, such as product bundling or promotions aimed at frequently associated items. Additionally, the insights can support more efficient inventory management by forecasting demand for co-occurring products, thereby minimizing overstock or shortages. The system's functionality and validity were confirmed through black-box testing, demonstrating its usability and alignment with user requirements. For future research, it is recommended to extend the analysis to cover longer transaction periods to capture seasonal trends and evolving customer behaviors. Comparative studies using other association algorithms such as Apriori or Eclat are also suggested to evaluate performance differences and explore alternative insights, thereby enhancing the robustness and applicability of data mining in cooperative environments

## ACKNOWLEDGEMENTS

We extend our highest appreciation to all parties who have contributed to the completion of this research. In particular, we would like to express our gratitude to our colleagues for their constructive feedback, continuous support, and encouragement throughout the research process. We also sincerely thank all participants who generously dedicated their time and provided valuable input for this study. Our appreciation is likewise directed to the institutions and organizations that have provided essential support and facilities during the implementation of this research. Every form of assistance and contribution has played a vital role in ensuring the smooth progress and success of this work.

## REFERENCES

Anggrawan, A., Mayadi, M., & Satria, C. (2021). Menentukan Akurasi Tata Letak Barang dengan Menggunakan Algoritma Apriori dan Algoritma FP-Growth. *MATRIK : Jurnal Manajemen, Teknik Informatika Dan Rekayasa Komputer*, *21*(1), 125–138. https://doi.org/10.30812/matrik.v21i1.1260

Arifandy, F. P., Norsain, N., & Firmansyah, I. D. (2020). Peran Koperasi Dalam Meningkatkan Perekonomian Masyarakat Nelayan: Perspektif Modal Kerja. *Jurnal Akademi Akuntansi*, *3*(1), 118. https://doi.org/10.22219/jaa.v3i1.11665

Ashari, I. A., Wirasto, A., Nugroho Triwibowo, D., & Purwono, P. (2022). Implementasi Market Basket Analysis dengan Algoritma Apriori untuk Analisis Pendapatan Usaha Retail. *MATRIK : Jurnal Manajemen, Teknik Informatika Dan Rekayasa Komputer*, *21*(3), 701–709. https://doi.org/10.30812/matrik.v21i3.1439

De Wibowo Muhammad Sidik, A., Himawan Kusumah, I., Suryana, A., Artiyasa, M., & Pradiftha Junfithrana, A. (2020). Gambaran Umum Metode Klasifikasi Data Mining. *FIDELITY : Jurnal Teknik Elektro*, *2*(2), 34–38. https://doi.org/https://doi.org/10.52005/fidelity.v2i2.111

Djabalul Lael, T. A., & Pramudito, D. A. (2023). Use of Data Mining for The Analysis of Consumer Purchase Patterns with The Fpgrowth Algorithm on Motor Spare Part Sales Transactions Data. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, *4*(2), 128–136. https://doi.org/10.34306/itsdi.v4i2.582

Etiowo, G., & Okoronkwo, J. M. C. (2023). A Brief Survey: Data Mining Techniques and Application on Selected Sectors. *International Journal of Innovative Science and Research Technology*, *8*(6), 1014–1018. https://doi.org/https://doi.org/10.5281/zenodo.8093226

Firmansyah, F., & Nurdiawan, O. (2023). Penerapan Data Mining Menggunakan Algoritma Frequent Pattern - Growth Untuk Menentukan Pola Pembelian Produk Chemicals. *JATI: Jurnal Mahasiswa Teknik Informatika*, *7*(1), 547–551. https://doi.org/10.36040/jati.v7i1.6371

Gulo, F. E., Azhari, F. A., Setiawan, L., & Pratiwi, L. A. (2023). Penerapan Aturan Asosiasi di Darvina Mart untuk Menentukan Pola Pembelian Pelanggan. *Journal of Industrial Innovation and Safety Engineering (JINSENG)*, *1*(2), 92–100. https://doi.org/10.35718/jinseng.v1i2.897

Hakim, M. A., Prasetijo, A. B., & Eridani, D. (2023). Penerapan Data Mining Dengan Algoritma K-Means Clustering Penyewaan Alat-Alat Event Pada Studi Kasus CV. Dipo Rental Creativindo. *Jurnal Teknik Komputer*, *1*(4), 148–155. https://doi.org/10.14710/jtk.v1i4.37011

Handayani, P. K., & Susanti, N. (2019). Analisis Kinerja Algoritma Frequent Pattern Growth (FP-Growth) Pada Penambangan Pola Asosiasi Data Transaksi. *Indonesian Journal of Technology, Informatics and Science (IJTIS) DOI: …*, *1*(1), 9–12. https://doi.org/https://doi.org/10.24176/ijtis.v1i1.4596

Handayani, T., Sunaryo, M. A., Rinaldi, A. R., & Rohmat, C. L. (2024). Analisis Minat Beli Produk Fashion Menggunakan Algoritma FP-Growth (Frequent Pattern Grwoth). *Jurnal Ilmiah Informatika Komputer*, *29*(1), 83–93. https://doi.org/10.35760/ik.2024.v29i1.10808

Herdyansyah, S., Hermaliani, E. H., Kurniawati, L., & Sri Rahayu, S. R. (2020). Analisa Metode Association Rule Menggunakan Algoritma Fp-Growth Terhadap Data Penjualan (Study Kasus Toko Berkah). *Jurnal Khatulistiwa Informatika*, *8*(2), 127–133. https://doi.org/10.31294/jki.v8i2.9277

Lintang, & Lestari, M. (2023). Penerapan Algoritma FP-Growth Untuk Menentukan Pola Penjualan Toko Ellia Umami. *Journal of Student Research (JSR)*, *1*(3), 367–378. https://doi.org/https://doi.org/10.55606/jsr.v1i3.1267

Mariko, M. (2021). Perbandingan Algoritma Apriori Dan Algoritma Fp-Growth Untuk Rekomendasi Item Paket Pada Konten Promosi. *Explore*, *11*(2), 24–28. https://doi.org/10.35200/explore.v11i2.438

Octaviani, A., & Dewi, P. (2020). Big Data di Perpustakaan dengan Memanfaatkan Data Mining. *Anuva: Jurnal Kajian Budaya, Perpustakaan, Dan Informasi*, *4*(2), 223–230. https://doi.org/https://doi.org/10.14710/anuva.4.2.223-230

Purba, T. N., & Firdaus, D. (2021). Determination for Consumer Patterns in Beverage Product Sales Using the Frequent Pattern Growth Algorithm. *IJISCS: International Journal of Information System and Computer Science*, *5*(2), 84–92. https://doi.org/10.56327/ijiscs.v5i2.982

Rahayu, N. D., Anshor, A. H., Afriantoro, I., & Halim Anshor, A. (2024). Penerapan Data Mining untuk Pemetaan Siswa Berprestasi menggunakan Metode Clustering K-Means Oleh : Penerapan Data Mining untuk Pemetaan Siswa Berprestasi menggunakan Metode Clustering K-Means. *JUKI : Jurnal Komputer Dan Informatika*, *6*(1), 71–73. https://doi.org/https://doi.org/10.53842/juki.v6i1.474

Septiandito Saputra, A. (2021). Pengaruh Teknologi Informasi Pada Koperasi Di Era Industri 4.0. *Transekonomika: Akuntansi, Bisnis Dan Keuangan*, *1*(5), 505–510. https://doi.org/10.55047/transekonomika.v1i5.77

Setiaji, Akbar, F., Abdillah, A., & Fachrizal, J. (2024). Implementasi Model Unified Modelling Language (UML) Pada Perancangan Sistem Informasi Data Kependudukan dan Bantuan Sosial. *Jurnal Informatika Teknologi Dan Sains*, *6*(3), 549–558. https://doi.org/https://doi.org/10.51401/jinteks.v6i3.4305

Supriyadi, D. (2020). Penerapan Association Rule Mining Berbasis Algoritma Frequent Pattern Growth untuk Rekomendasi Penjualan. *JATISI: Jurnal Teknik Informatika Dan Sistem Informasi*, *7*(2), 135–148. https://doi.org/10.35957/jatisi.v7i2.339

Takdirillah, R. (2020). Penerapan Data Mining Menggunakan Algoritma Apriori Terhadap Data Transaksi Sebagai Pendukung Informasi Strategi Penjualan. *Edumatic : Jurnal Pendidikan Informatika*, *4*(1), 37–46. https://doi.org/10.29408/edumatic.v4i1.2081

Wandri, R., & Hanafiah, A. (2022). Analysis of Information Technology (IT) Goods Sales Patterns Using the FP-Growth Algorithm. *IT Journal Research and Development*, *6*(2), 130–141. https://doi.org/10.25299/itjrd.2022.8155

Wijaya, K. N. (2020). Analisa Pola Frekuensi Keranjang Belanja Dengan Dengan Perbandingan Algoritma Fp-Growth (Frequent Pattern Growth) dan Eclat pada minimarket. *JATISI: Jurnal Teknik Informatika Dan Sistem Informasi*, *7*(2), 364–373. https://doi.org/10.35957/jatisi.v7i2.380

Wijaya, K. N., Firsandaya Malik, R., Nurmaini, S., Komputer, M. I., Ilmu, F., & Unsri, K. (2020). Analisa Pola Frekuensi Keranjang Belanja Dengan Perbandingan Algoritma Fp-Growth (Frequent Pattern Growth) Dan Eclat Pada Minimarket. *Jurnal Teknik Informatika Dan Sistem Informasi*, *7*(2), 364–4322. https://doi.org/https://doi.org/10.35957/jatisi.v7i2.380

Yanti, R., Maradjabessy, P. N., Qurtubi, & Rachmadewi, I. P. (2024). Determining the retail sales strategies using association rule mining. *International Journal of Advances in Applied Sciences*, *13*(3), 530–538. https://doi.org/10.11591/ijaas.v13.i3.pp530-538