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Consumer Purchasing Pattern Analysis Using the FP-Growth Algorithm for Inventory Availability in MSMEs

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Abstract

Inventory management in fruit and vegetable distribution businesses faces challenges due to the perishable nature of products and fluctuations in consumer demand. Suboptimal inventory management can lead to overstock or stock shortages, while sales transaction data are often underutilized in decision-making. At Induk Buah & Sayur (IBS), sales and inventory records are still managed using Microsoft Excel, limiting the identification of consumer purchasing patterns. This study aimed to analyze consumer purchasing patterns using the Frequent Pattern Growth (FP-Growth) algorithm to support inventory management. The study applied the Knowledge Discovery in Databases (KDD) methodology, including data collection, preprocessing, data transformation, frequent itemset generation, association rule mining, and evaluation using support, confidence, and lift ratio. The analysis conducted with RapidMiner, produced association rules with a confidence level above 80% and a lift ratio of more than 1. This indicates a significant positive relationship between products frequently purchased by customers. The results demonstrate that the FP-Growth algorithm effectively identifies consumer purchasing patterns to support inventory planning, optimize stock availability, reduce the risk of over.

Keywords: *FP-Growth, Knowledge Discovery in Databases, consumer purchasing patterns, association rules, inventory management.*

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INTRODUCTION

Swift progress in information technology has changed numerous facets of life, such as business management and enhancing public services in regional libraries (Nenat et al., 2025). In the digital age, the retail and food sectors encounter heightened competition, rendering consumer preference analysis essential for sustaining business operations (Junaedi et al., 2024). A significant amount of information from sales transaction data is merely kept as operational records without being transformed into strategic insights for the organization (Afriyani & Ali, 2023). Leveraging historical transaction data is essential for crafting marketing strategies, enhancing inventory control, and reducing losses from impaired products (Pratiwi et al., 2023). Numerous research efforts indicate that transaction data serves as a vital resource for organizations and can support strategic business decision-making when

2 examined with suitable data mining approaches (Musdalifah & Jananto, 2022; Putra et al., 2024). In the food industry, applying the FP-Growth algorithm to analyze customer buying habits enables business owners to customize promotions and menu options, greatly enhancing sales and operational efficiency. Analyzing retail cosmetics sales data enables companies to create tailored product packages as a component of a focused marketing strategy.

14 A key method in data mining for handling extensive transaction data is association rules, which aim to identify connections between combinations of item (Afriyani & Ali, 2023). The FP-Growth algorithm is a popular approach known for its efficiency in generating frequent item sets through an FP-Tree structure, avoiding the need for a complicated set of candidate items. This approach has shown great success in creating particular guidelines from sales data for inventory forecasting. In contrast to traditional algorithms like Apriori, FP-Growth outperforms in memory utilization and processing speed when handling large datasets. Research utilizing bakery sales data indicates that FP-Growth uses considerably less memory (0.08 MiB) compared to Apriori (45.36 MiB) (Hery & Widjaja, 2024). The scalability benefit arises from FP-Growth's direct utilization of the FP-Tree structure to locate frequent item sets and completely omits candidate generation, a phase that frequently leads to the slowdown of the Apriori algorithm as the number of item combinations rises. Previous comparative studies indicate that FP-Growth produces a higher quantity of association rules with stronger rule strength compared to Apriori, thus making it more advantageous for aiding decision-making in sales tactics (Musdalifah & Jananto, 2022). The execution of this algorithm is based on assessing the minimum support threshold, minimum confidence level, and lift ratio to ascertain the robustness of consumer buying behaviors (Pratiwi et al., 2023). The scalability of FP-Growth enables its application in different industries beyond retail, including mining 10 million blockchain address categories to discover patterns and anomalies in network behavior (Lenus, 2025). And analyzing more than 8,000 Solid-State Drive (SSD) error records to enhance customer service strategies and quality control in production (Chang et al., 2021)

1 25 Earlier studies have effectively implemented the FP-Growth algorithm across different domains. In the retail industry, FP-Growth has been employed to discover patterns and connections in consumer behavior, allowing management to create better inventory policies and enhance marketing strategies, similar to what occurred at Heron Store. In the fashion retail industry, a study on the G.I.B Store in Cimahi effectively employed FP-Growth on 1,025 online and offline transactions during 2023 to uncover important product relationships. The research revealed a 77.91% confidence level of correlation between specific premium clothing products, directly reinforcing boosted sales, promotional coherence, and enhanced inventory control. A separate retail analysis of 371 transactions from distribution outlets under different minimum support conditions (1%, 2%, and 3%) revealed that FP-Growth consistently produces accurate association rules, aiding business owners in creating successful up-selling and cross-selling approaches. Comparable achievements occurred in the culinary sector, where analyzing 960 transaction records from a juice and soup establishment uncovered consumer preference patterns, thereby enhancing sales and product placement strategies. At the MSME level, like Cafe Over Limit, FP-Growth examines numerous transactions to suggest suitable menu packages for clients, thus accelerating ordering processes (Hasan et al., 2023). A study at Ayam Geprek Purwokerto employed FP-Growth to determine the frequent product combinations such as white rice usually combined with chicken breast and iced tea—allowing the store to optimize inventory management, stimulate impulse purchases through strategic initiatives, and design appealing combo packages. In the processed food manufacturing industry, especially at PT

Kusno Baso, FP-Growth is implemented in the CRISP-DM framework to create cross-selling strategies aimed at resolving product accumulation and sales reductions caused by unsold stock (Prasetyo & Hasugian, 2023). The use of FP-Growth at Lia Store showed that analyzing transaction patterns greatly enhanced operational efficiency by assisting in inventory control and marketing approaches through the identification of meaningful purchasing relationship (Talia et al., 2024).

FP-Growth has been effectively applied in educational settings, like the Bina Mulia School Cooperative, to forecast office supplies inventory, allowing management to swiftly determine sales strategy choices. In the medical field, FP-Growth has been utilized to enhance the management of inventory. This occurrence was noted at a clinic in Brebes Regency, where 2,071 drug transactions were examined to identify association rules for drug utilization. FP-Growth has also shown its effectiveness in the creative sector. The Buulolo Gallery devised a woodcarving sales approach to optimize warehouse inventory and created marketing materials targeted at international tourists (Ndruru et al., 2022). A tech store assessed daily sales data to uncover valuable insights and create better marketing strategies for IT good (Wandri & Hanafiah, 2022). In the building materials sector, research on consumer purchasing behaviors at a building materials shop indicated that FP-Growth surpassed the Apriori algorithm and the Squeezer clustering technique in effectively creating association rules (Syaifulloh et al., 2024). Aside from commercial uses, FP-Growth is utilized in non-retail industries, including identifying electricity theft and coding government inventories, showcasing its skill in revealing concealed patterns from extensive transaction datasets to aid operational decision-making (Almira et al., 2021; Sari et al., 2024).

Literature reviews in the last five years show a large research gap, as the majority of existing studies only use short-term data covering transactions over one month (Junaedi et al., 2024; Khadijah & Waluyo, 2024; Pratiwi et al., 2023). More comprehensive studies have shown that using historical data spanning two years can generate more accurate marketing strategies (Prasetyo & Hasugian, 2023). Previous datasets have limited the association patterns generated to capture seasonal fluctuations and long-term changes in consumer behavior (Saputro & Nugraha, 2023). No comprehensive study has integrated physical library layout optimization with a comparative analysis of algorithms and association rules to validate the stability of the resulting rules (Nenat et al., 2025). To address these methodological limitations, this study aims to fill the identified scientific gap by analyzing transaction data over a longer and more diverse historical period (Afriyani & Ali, 2023). The scientific study of this research is to dynamically evaluate association parameters so that inventory management decisions are vulnerable to temporal data bias (Zarkashy et al., 2024). The main objective of this research is to identify the most significant item combinations for optimizing operational processes and intelligent product placement (Gunia et al., 2024). This goal aligns with recent studies showing that FP-Growth offers association rules for long-term business planning by efficiently processing large transaction datasets while maintaining computational efficiency (Jang et al., 2021; Putra et al., 2024). The novelty of this study lies in establishing a framework for sustainable association pattern discovery, linking the algorithm's theoretical accuracy with long-term practical applications across diverse sectors.

METHOD

This study utilizes the Knowledge Discovery in Databases (KDD) framework along with the FP-Growth algorithm to analyze consumer spending patterns using sales transaction data from Induk Buah & Sayur (IBS). The research process consists of five stages: data collection, data pre-processing, FP-Growth application, association rule creation, and result evaluation, as shown in Figure 1.

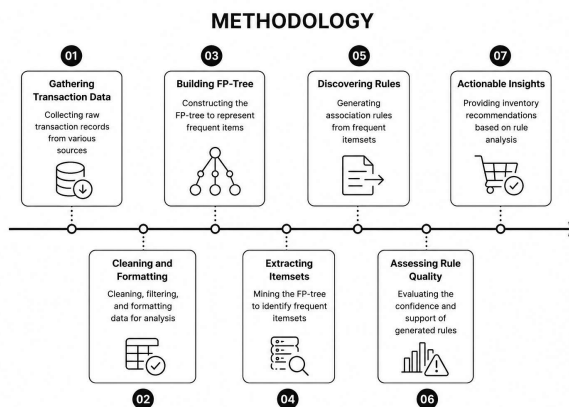


Figure 1. Data Mining Process

This dataset contains **100 sales transaction** records obtained from Induk Buah & Sayur (IBS). Each transaction contains information about the products purchased by consumers and serves as the primary data set for association rule mining. Transaction data is checked for completeness and consistency before further processing.

Data preprocessing includes **data cleaning, data sorting, and data transformation**. Data cleaning removes incomplete transaction entries. Data sorting preserves attributes important for purchasing pattern analysis, while data transformation converts the transaction data into a binary matrix, where a value of **1** indicates a purchased product and a value of 0 indicates otherwise. This preprocessing ensures the data is suitable for FP-Growth analysis..

In the preprocessing stage, the FP-Growth algorithm is applied to construct an FP-Tree and generate frequently occurring itemsets. The analysis is performed with a **minimum support threshold of 0.85 (85%)** and a **minimum confidence threshold of 0.85 (85%)**. These frequent itemsets are used to generate association rules, evaluated using **support, confidence, and lift ratio** to determine the relationship between products.

This analysis uses **RapidMiner Studio**, which facilitates the implementation of the FP-Growth algorithm, the creation of association rules, the calculation of support, confidence, and lift ratio values. Association rules are generated and interpreted as inventory recommendations that support stock optimization, reduce the risk of overstocking and understocking, and improve data driven decision making.

RESULTS AND DISCUSSION

Results

This research began with the collection of sales transaction data from Induk Buah & Sayur (IBS). The data was selected to retain relevant attributes and transformed into a binary matrix, where 1 indicates that a product was purchased and 0 indicates that it was not. This transformation allowed the data to be processed using the FP-Growth algorithm to identify associations between products..

Table 1. Binary Representation of Sales Transaction Data

Customer	Honeydew	Chili	Mushroom	Potato	Orange	Tomato	Shallot
1	0	1	1	1	1	1	1
2	0	1	0	1	1	1	1
3	0	1	1	1	1	1	1
4	0	1	0	1	1	1	1
5	0	1	1	1	1	1	1
....							
100	1	0	1	0	0	0	0

After generating a set of frequently occurring items using the FP-Growth algorithm, the next step is to generate **association rules** to identify relationships between frequently purchased products. The quality of association rules has three main measures: **support, confidence, and lift ratio**. Support indicates how frequently a product combination appears in the transaction database, confidence measures the reliability of the association rule, and lift ratio evaluates the strength of the relationship between products. An example of association rule calculation is shown using the rules **Red Onion and Orange → Chili**.

A. Support

$$\text{Support}(A) = \frac{\sum \text{Transactions Containing } A}{\text{Total Transactions}} \quad (1)$$

The association rule for **Shallots and Oranges → Chilies** is that the combination of Shallots, Oranges, and Chilies appears in 19 out of 100 transactions. Therefore, the support value is calculated as follows:

$$\text{Support}(A) = \frac{19}{100} = 0.190 = 19\%$$

The support value of **0.190 (19%)** indicates that this combination appears in **19%** of all transactions.

B. Confidence

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)} \quad (2)$$

The combination of **red onion and orange** appears in 19 transactions, all of which contain chili. Therefore, the trust value is calculated as follows:

$$\text{Confidence}(\text{Shallot, Orange} \rightarrow \text{Chilli}) = \frac{0.190}{0.190} = 1.000 = 100\%$$

A confidence level of **1,000 (100%)** indicates that every transaction containing Red Onions and Oranges also contains Chilies, indicating a perfect association.

C. Lift Ratio

$$Lift(A \rightarrow B) = \frac{Confidence(A \rightarrow B)}{Support(B)} \quad (3)$$

Chile's support value is **0.670**, while its confidence value is **1.000**. The lift ratio is calculated as follows:

$$Lift(Shallot, Orange \rightarrow Chili) = \frac{1.000}{0.670} = 1.493$$

The lift ratio of **1.493** indicates a positive association because the lift value is greater than 1. This result indicates that customers who buy Red Onions and Oranges are more likely to buy Chilies than expected by chance. These rules can be used as guidelines for inventory management suggestions.

In assessing the association rules generated by the FP-Growth algorithm, this study uses three main measures: **support, confidence, and lift ratio**. Support is used to determine the frequency of an item or combination of items in the entire transaction dataset. Confidence measures association rules by indicating the probability that the consequent item will be purchased when the antecedent item has been purchased. Lift ratio is used to evaluate the strength of the relationship between products by comparing the confidence value with the probability of the occurrence of the consequent item. A lift ratio greater than 1 indicates a positive association and a strong relationship between products, indicating that association rules can serve as a basis for inventory stock recommendations.

Table 2. Recapitulation of Product Transaction Frequency

No	Item	Support	Quantity
1	Shallot	69.0%	69
2	Chili	67.0%	67
3	Mushroom	53.0%	53
4	Tomato	52.0%	52
5	Potato	32.0%	32
6	Orange	27.0%	27
7	Honeydew	7.0%	7

In Table 2, the support values indicate the frequency of each product's appearance in sales transactions. Shallots had the highest support value (69.0%), followed by chilies (67.0%), while honeydew melon had the lowest support value (7.0%). Products with higher support values generated more frequently occurring itemsets and formed significant association rules in the FP-Growth analysis.

Table 3. Association Rules of Customer Purchasing Patterns

No	Rule	Support	Confidence	Lift Ratio
1	If a customer purchases Mushroom and Potato then the customer will purchase Chili .	18/100 = 18.0%	18/20 = 90.0%	1.343

2	If a customer purchases Tomato and Potato , then the customer will purchase Chili .	$27/100 = 27.0\%$	$27/30 = 90.0\%$	1.343
3	If a customer purchases Chili and Orange , then the customer will purchase Shallot .	$19/100 = 19.0\%$	$19/21 = 90.5\%$	1.311
4	If a customer purchases Potato , then the customer will purchase Chili .	$29/100 = 29.0\%$	$29/32 = 90.6\%$	1.353
5	If a customer purchases Shallot , Chili , and Potato , then the customer will purchase Tomato .	$24/100 = 24.0\%$	$24/26 = 92.3\%$	1.775
6	If a customer purchases Shallot and Potato , then the customer will purchase Tomato .	$25/100 = 25.0\%$	$25/27 = 92.6\%$	1.781
7	If a customer purchases Chili and Potato , then the customer will purchase Tomato .	$27/100 = 27.0\%$	$27/29 = 93.1\%$	1.790
8	If a customer purchases Potato , then the customer will purchase Tomato .	$30/100 = 30.0\%$	$30/32 = 93.8\%$	1.803
9	If a customer purchases Mushroom and Potato , then the customer will purchase Tomato .	$19/100 = 19.0\%$	$19/20 = 95.0\%$	1.827
10	If a customer purchases Shallot , Tomato , and Potato , then the customer will purchase Chili .	$24/100 = 24.0\%$	$24/25 = 96.0\%$	1.433
11	If a customer purchases Shallot and Potato , then the customer will purchase Chili .	$26/100 = 26.0\%$	$26/27 = 96.3\%$	1.437
12	If a customer purchases Shallot and Orange , then the customer will purchase Chili .	$19/100 = 19.0\%$	$19/19 = 100\%$	1.493

Table 3 shows the association rules generated by the FP-Growth algorithm by applying minimum support and confidence thresholds. The results indicate a strong relationship between

products, as indicated by confidence values ranging from **90.0%** to **100%** and a lift ratio greater than **1**. The most robust association rule is Shallots and Oranges → Chilies, boasting a 100% confidence and a 1.493 rise in the association ratio, signifying that buyers of Shallots and Oranges are likely to buy Chilies as well. This association rule offers important insights into consumer spending behaviors and can guide inventory management choices.

Discussion

The application of the FP-Growth algorithm revealed notable buying trends from sales transaction data at Induk Buah & Sayur (IBS). The derived association rules show that multiple products are regularly bought together, highlighting a consistent pattern in consumer buying behavior. Shallots and oranges → chilies exhibit a confidence level of 100%, with each generated rule yielding a lift ratio exceeding 1, indicating a positive correlation among these items. This shows that the recognized buying patterns are important and can aid in inventory management.

A theoretical viewpoint consistent with the tenets of **Association Rule Mining** within the realm of **Knowledge Discovery in Databases (KDD)** highlights the retrieval of concealed knowledge from extensive transaction datasets. A positive lift ratio suggests that the detected product combinations occur more often than would be anticipated by randomness, reflecting a notable relationship in buying behavior compared to random events. This verifies that transaction details can be converted into significant privacy to aid business choices and inventory control.

These findings correspond with earlier studies showcasing the effectiveness of the FP-Growth algorithm in identifying shopping behaviors in different retail sectors. Prior studies have employed FP-Growth to enhance promotional strategies, product bundling, and sales optimization. This research expands its application to the fruit and vegetable distribution field, where managing inventory is more challenging because of the products' perishable characteristics. The identified association rules provide valuable insights that enhance availability by pinpointing products that require simultaneous monitoring and restocking.

The analysis revealed no unexpected or inconsistent association patterns. Every association rule generated lift ratios exceeding 1, demonstrating a steady positive correlation between associated products. This suggests that buyer purchasing patterns in IBS are stable enough to enable stock planning informed by association rules. The lack of negative correlations suggests that the resulting guidelines can be trusted for practical decision-making.

This research adds to the current understanding by presenting proof that the FP-Growth algorithm is applicable not just for marketing analysis but also for inventory management in small and medium enterprises handling perishable goods. These results bolster the practical execution of association rule mining by showcasing that past transaction information can be utilized to enhance inventory management and facilitate data-informed operations choices.

From a practical standpoint, the generated association rules can assist business owners enhance stock management and ensure product accessibility. Items that commonly arise together ought to be restored concurrently to reduce the likelihood of deficits. Recognized

Buying behaviors can be utilized to create product bundling approaches, enhance product positioning, and improve marketing efforts according to real customer buying patterns.

This research focuses on sales transaction information obtained from one company over a brief observation duration. The recognized buying habits might not completely reflect consumer conduct in different retail settings. Future studies are advised to examine larger, more varied datasets gathered over an extended timeframe to combine association rule mining with analytic forecasting or machine learning methods to enhance inventory management and choices assistance frameworks

CONCLUSION

This research shows that using the FP-Growth algorithm effectively derives significant buying trends from the sales transaction records of Induk Buah & Sayuran (IBS). The recognized association rules offer important insights into commonly bought product combinations, allowing for a more structured examination of customer buying conduct. These results advocate for utilizing transaction data as a foundation for inventory planning and availability oversight.

This study adds to the use of association rule mining for the management of perishable produce, where precise inventory control is essential to minimize stock shortages and excess inventory. The recognized buying trends offer recommendation for ensuring product availability and enhancing inventory control tactics informed by real customer buying actions.

This research is constrained by the reliance on transaction information from one company over a comparatively brief duration, which could influence the applicability of the results. Subsequent research are advised to examine more extensive and varied data sets, incorporate several retail locations, and incorporate forecasting methods to enhance inventory management and decision-making assistance. In general, this research verifies that information gathered from sales transactions Data can enhance more efficient inventory management and aid in data-driven decisions. decision-making within retail companies.

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