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Exploring Customer Purchasing Patterns: A Study Utilizing FP-Growth Algorithm on Supermarket Transaction Data

Hairani Hairani[1], Juvinal Ximenes Guterres[2]
[1]Universitas Bumigora, Mataram, Indonesia
[2]Universidade Oriental Timur Lorosa'e, Unital Becora Dili, Timor Leste

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ABSTRACT

The need to analyze consumer purchasing patterns using association techniques also lies in the increasingly fierce competition in the retail market. Supermarkets face the challenge of understanding their customers' buying patterns. By utilizing association techniques, supermarkets can identify customer buying trends and quickly and appropriately adjust their strategies. Thus, analyzing consumer purchasing patterns using association techniques is no longer an option but an urgent need for supermarkets that want to survive and thrive in a changing market. Therefore, **this study aimed** to analyze purchasing patterns in supermarkets using the FP-Growth method to understand purchasing behavior and identify relevant patterns from transaction data. **The method used** in this research was the FP-Growth association method to create association rules from customer transaction data. **The findings of this research** were the use of the FP-Growth method in analyzing supermarket customer purchasing patterns, which obtained 10 association rules for 2 itemsets and 11 association rules for 3 itemsets based on a minimum Support value of 30% and a minimum Confidence of 70%. The association rules generated by the FP-Growth method on 2 itemsets and 3 itemsets simultaneously bring up items often purchased by customers with the same pattern, namely Cooking Oil, Eggs, Flour, and Candy. **This research concludes** that the association rules formed can be used as a benchmark by supermarkets in preparing stock items and making strategies to increase sales for more profit.

Corresponding Author:

Hairani Hairani,
Universitas Bumigora, Mataram, Indonesia.
Email: Hairani@universitasbumigora.ac.id

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1. INTRODUCTION

Analyzing consumer purchasing patterns in supermarkets poses a significant challenge in the modern era of retail trade [1, 2]. With the increasing number of items available on shelves, it is crucial to understand how customer buying behavior evolves over time [3, 4]. The primary issue supermarket managers face is difficulty tracking complex and ever-changing purchasing patterns [5]. Without a profound understanding of these patterns, supermarkets may struggle to plan inventory efficiently, arrange optimal store layouts, and adjust pricing strategies [6]. In this context, analyzing consumer purchasing patterns using association techniques becomes crucial [7, 8]. For instance, supermarkets may discover that customers buying milk also tend to purchase bread. Such information can be utilized to formulate more effective promotional packages or optimize store layouts to enhance sales [9].

The need to analyze consumer purchasing patterns using association techniques also lies in the increasingly fierce competition in the retail market. With online stores and delivery services growing in popularity, supermarkets must be able to face the competition by deeply understanding their customers' preferences [10]. By utilizing association techniques, supermarkets can identify evolving purchasing trends and quickly and appropriately adjust their strategies [11]. Thus, analyzing consumer purchasing patterns using association techniques is no longer an option but an urgent need for supermarkets that want to survive and thrive in the ever-changing market [12].

The utilization of association techniques in consumer purchasing pattern analysis has been conducted in several prior studies. For instance, research [13] employed both the Apriori and FP-Growth methods to analyze outdoor product sales transactions to determine patterns and relationships within the transactions. This study applied a minimum support value of 29.6% and a minimum confidence value of 75%. The Apriori method yielded 10 association rules, while the FP-Growth method produced 4 rules. Another study [14] focused on movie recommendation systems using the Apriori and FP-Growth algorithms. The research findings indicated that Apriori and FP-Growth methods yielded the same 10 association rules. Yet, the FP-Growth algorithm exhibited faster rule formation than the Apriori algorithm. Research [15] also applied the FP-Growth method for product stock management, revealing 9 association rules based on a minimum support value of 30% and a minimum confidence value of 70%.

Research [15] analyzed customer purchasing patterns in sales transaction data using the Apriori method. The findings revealed that the Apriori method generated 26 association rules based on a minimum support value of 2% and a minimum confidence value of 50%. Research [16] also focused on inventory management using the Apriori and FP-Growth methods. The results showed that the Apriori and FP-Growth methods produced the same number of association rules, namely 16, based on a minimum support value of 20%. Furthermore, research [17] utilized the FP-Growth method for designing product placements based on customer purchasing patterns. The findings demonstrated that the FP-Growth method could generate 6 association rules based on a minimum support value of 90% and a minimum confidence value of 80%. Lastly, research [16] employed the Apriori method for product stock management, revealing that the Apriori method yielded 6 association rules based on a minimum support value of 50% and a minimum confidence value of 60%.

Based on the previous research, the FP-Growth method has proven more reliable in generating association rules from transactional data and exhibits efficiency in rule generation [18, 19]. Therefore, this study applies the FP-Growth method to analyze consumer purchasing patterns using supermarket sales data, aiming to effortlessly identify relationships between items frequently purchased together by customers. FP-Growth is a data processing technique that enables the identification of frequently occurring patterns in a set of transactional data [20]. **The primary objective of this research** is to analyze customer purchasing patterns in supermarkets using the FP-Growth method to comprehend customer buying behavior and identify relevant patterns from transactional data. The anticipated **contribution of the research** findings is to assist in discovering consumer purchasing patterns, enabling supermarkets to develop innovative promotional and sales strategies to attract new customers or increase the spending of existing ones.

2. RESEARCH METHOD

This research comprises several stages, as illustrated in Figure 1. The first stage involves data collection. The study utilizes product transaction data from a supermarket obtained from the Kaggle website. The dataset consists of 350 transactions involving 9 items: Detergent, Soy Sauce, Cooking Oil, Candy, Soap, Snack, Milk, Flour, and Eggs. The second stage involves data processing, a crucial aspect of the association data mining process, as this phase forms the basis for discovering meaningful patterns and relationships within the transactional dataset. Proper data processing ensures that mining algorithms can effectively identify relevant association rules that can be used for decision-making and knowledge discovery from a set of transactional data. One of the data processing methods utilized in this stage is data transformation. Data transformation is a significant processing method used in this phase. This process plays a vital role in converting transactional data into a suitable format for association rule mining. Through data transformation, textual items are systematically converted into numeric representations and organized into a tabular structure.

By arranging data in this manner, the FP-Growth method, renowned for its efficiency in handling large datasets, can be employed to extract customer shopping patterns from transactional data, enabling in-depth analysis and decision-making for future strategy formulation.

The FP-Growth method (Frequent Pattern Growth) is a popular algorithm in data mining for generating association rules within a set of transactional data. Furthermore, the FP-Growth method is widely employed in market basket analysis, recommendation systems, and sequential pattern mining. The primary advantage of the FP-Growth method lies in its efficiency in handling large datasets with high dimensions [21]. Constructing an FP-Tree and avoiding the generation of candidate itemsets significantly reduces computational time compared to methods like Apriori, particularly when dealing with large amounts of sparse data [22].

After implementing the FP-Growth method, performance measurement of the generated rules is essential. Commonly used performance metrics for association rule tasks include Support, Confidence, and Lift Ratio. Support indicates the frequency of occurrence of a specific item in the dataset. Confidence reflects how often a rule is confirmed to be true, thus indicating the reliability of the rule. Lift Ratio is employed to measure the confidence level of items appearing together if they are statistically independent [23]. The formulas for calculating the values of Support, Confidence, and Lift Ratio are respectively presented in Equations (1), (2) [24], and (3) [23].

$$Support\ (X) = \frac{Transaction\ Containing\ X}{Total\ Transaction} \tag{1}$$

$$Confidence\ (X \rightarrow Y) = \frac{Support(X \cup Y)}{Support\ X} \tag{2}$$

$$Lift\ Ratio\ (X \rightarrow Y) = \frac{Confidence\ (X \rightarrow Y)}{Support\ (Y)} \tag{3}$$

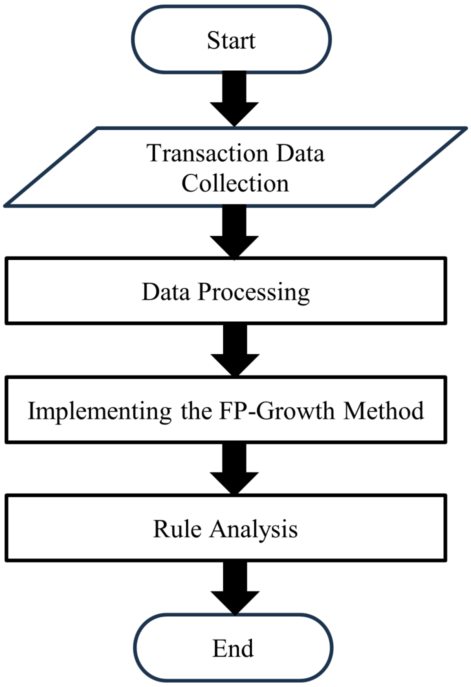

Figure 1. Research Flow

3. RESULT AND ANALYSIS

The author presents the comprehensive results and analysis obtained from exploring customer purchasing patterns using the FP-Growth algorithm in this section. The dataset utilized for this exploration is derived from supermarket transactions.

3.1. Data Collection

This research utilizes product transaction data from a supermarket obtained from the Kaggle platform. The dataset comprises 350 transactions involving 9 items: Detergent, Soy Sauce, Cooking Oil, Candy, Soap, Snack, Milk, Flour, and Eggs. The sales transactions data depicts varying percentages of each item sold, as illustrated in Figure 2. The sample transaction data is presented in Table 1.

Table 1. Item Transaction Data Sample

No	TID	Items
1	548252	Eggs, Cooking Oil, Candy, Flour
2	548253	Detergent, Soy Sauce, Milk, Soap
3	548530	Eggs, Cooking Oil, Soy Sauce, Snack, Candy, Flour
4	548436	Detergent, Soy Sauce, Soap
5	548442	Telur, Minyak, Kecap, Snack, Permen, Tepung
...	......	....
346	548423	Eggs, Cooking Oil, Soy Sauce, Snack, Candy, Flour
347	548239	Eggs, Detergent, Cooking Oil, Candy, Flour
348	548216	Eggs, Cooking Oil, Soap, Snack, Flour
349	548218	Eggs, Cooking Oil, Flour
350	548469	Eggs, Cooking Oil, Soap, Snack, Flour

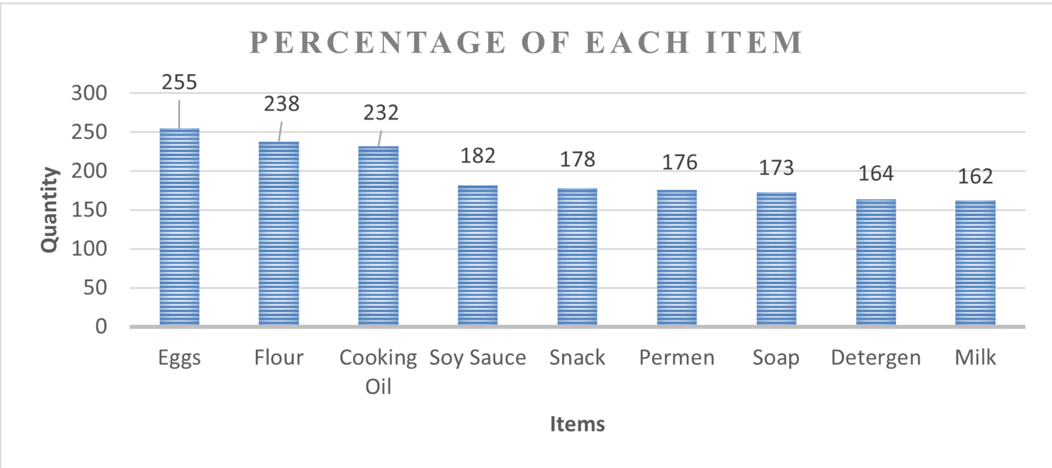

Figure 2. Percentage of Each Item

3.2. Processing Transaction Data

The transaction data in Table 1 is in its raw form, making it impractical to analyze purchasing patterns using the FP-Growth method. Therefore, it is necessary to transform the data, converting textual items into numeric representations and storing them in a tabular format, as illustrated in Table 2.

Table 2. Tabular Data of Transformation Result on Transaction Data

TID	Detergent	Soy Sauce	Cooking Oil	Candy	Soap	Snack	Milk	Eggs	Flour
548252	0	0	1	1	0	0	0	1	1
548253	1	1	0	0	1	0	1	0	0
548530	0	1	1	1	0	1	0	1	1
548436	1	1	0	0	1	0	0	0	0
548442	0	1	1	1	0	1	0	1	1
548400	1	0	1	1	1	1	0	1	1
548250	1	0	1	1	0	1	0	1	1

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TID	Detergent	Soy Sauce	Cooking Oil	Candy	Soap	Snack	Milk	Eggs	Flour
548367	0	1	0	1	1	1	0	1	0
548477	0	1	1	1	0	1	1	1	1
548486	1	1	1	0	0	0	1	1	1
...	...	...	...	...	...	...	...	...	...
10277	1	0	1	0	0	0	1	1	1
10020	0	1	1	0	1	1	1	1	1
10121	0	1	1	1	0	0	0	1	0
10005	0	1	1	0	1	0	0	0	1
10128	1	0	1	0	1	0	1	1	1
10218	1	0	1	0	0	0	0	1	1
10251	1	0	1	1	0	0	0	1	1
10342	0	0	1	0	1	1	0	1	1
10242	0	0	1	0	0	0	0	1	1
10167	0	0	1	0	1	1	0	1	1

3.3. FP-Growth Method Implementation

The implementation of the FP-Growth method in forming association rules on supermarket transaction data is carried out using the RapidMiner tool, as depicted in Figure 3. The process begins with reading the transaction data in Excel format, then converting numerical to binomial representation. Subsequently, the FP-Growth method is applied, resulting in the formation of association rules.

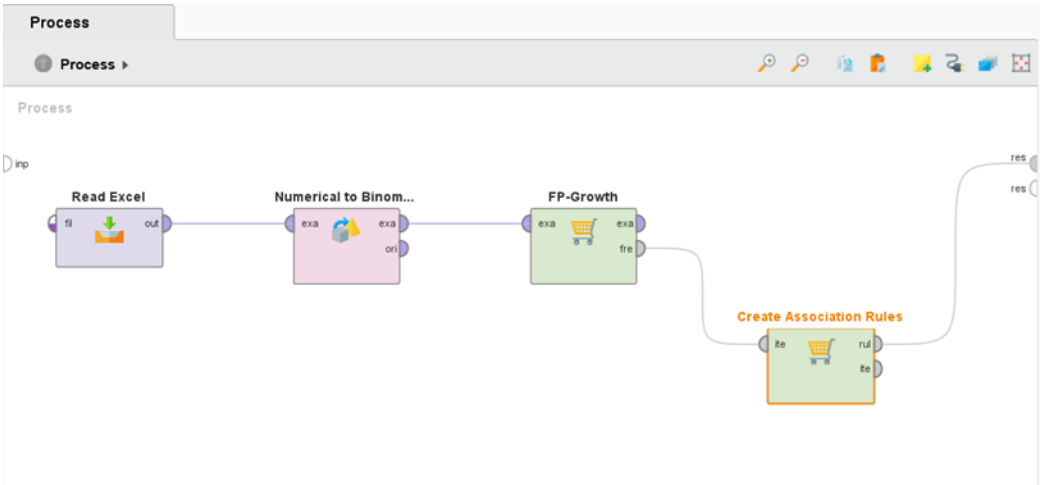

Figure 3. FP-Growth Method with RapidMiner

3.4. Rule Analysis of FP-Growth Method Implementation

An in-depth analysis of the association rules formed using the FP-Growth method is essential to comprehend customer purchasing patterns based on sales transaction data, employing both 2-item and 3-item set rules. Delving deeper into the established rules is crucial for uncovering hidden patterns within the sales transaction data. Analyzing customer purchasing patterns from sales transaction data enables supermarkets to gain valuable insights into the correlations between various products and unveil hidden relationships. These insights can inform strategic decision-making regarding the placement of frequently purchased items and the creation of packages that facilitate customer purchases, ultimately enhancing profitability for the supermarket.

Furthermore, a comprehensive analysis of the association rules formed using the FP-Growth method serves as a foundation for decision-making based on data. This approach enables the formulation of strategies to enhance customer satisfaction and loyalty. The association rules established through the FP-Growth method with 2-item sets are illustrated in Figure 3, while rules based on 3-item sets are presented in Table 4. The displayed association rules for both 2-item- and 3-item sets adhere to minimum values of 30% for Support, 70% for Confidence, and 1 for Lift Ratio.

Table 3. Results of Rules Formed with 2 Item Sets

No	Association Rules	Support	Confidence	Lift Ratio
1	If purchasing **Eggs**, then purchasing **Cooking Oil**	0,57	0,79	1,19
2	If purchasing **Cooking Oil**, then purchasing **Eggs**	0,57	0,87	1,19
3	If purchasing **Eggs**, then purchasing **Flour**	0,57	0,78	1,14
4	If purchasing **Flour**, then purchasing **Eggs**	0,57	0,83	1,14
5	If purchasing **Flour**, then purchasing **Cooking Oil**	0,53	0,77	1,17
6	If purchasing **Cooking Oil**, then purchasing **Flour**	0,53	0,79	1,17
7	If purchasing **Snack**, then purchasing **Eggs**	0,37	0,74	1,01
8	If purchasing **Candy**, then purchasing **Eggs**	0,37	0,74	1,02
9	If purchasing **Candy**, then purchasing **Cooking Oil**	0,37	0,73	1,11
10	If purchasing **Candy**, then purchasing **Flour**	0,36	0,71	1,04

Based on Table 3, using 2 item sets forms 10 association rules, with the most frequently appearing items being cooking oil, eggs, flour, and candy. The supermarket can recommend implementing sales strategies to enhance profitability by preparing a large quantity of the top 4 simultaneously purchased items, such as Eggs, Cooking Oil, Flour, and Candy. Apart from that, the association rules formed in Table 3 use the highest Support, namely a minimum of 50% and a minimum Confidence of 80%, which can recommend supermarkets to place Cooking Oil next to Eggs and also place Flour next to Eggs to make it easier for customers to search for goods. thus increasing sales. Not only that, supermarkets make packages by combining Cooking Oil with Eggs, or Flour with Eggs to support marketing strategies.

Table 4. Results of Rules Formed with 3 Item Sets

No	Association Rules	Support	Confidence	Lift Ratio
1	If purchasing **Flour** and **Cooking Oil**, then purchasing **Eggs**	0,49	0,92	1,27
2	If purchasing **Eggs** and **Flour**, then purchasing **Cooking Oil**	0,49	0,86	1,30
3	If purchasing **Eggs** and **Cooking Oil**, then purchasing **Flour**	0,49	0,85	1,24
4	If purchasing **Cooking Oil** and **Candy**, then purchasing **Eggs**	0,31	0,84	1,16
5	If purchasing **Eggs** and **Candy**, then purchasing **Cooking Oil**	0,31	0,83	1,26
6	If purchasing **Cooking Oil** and **Soy Sauce**, then purchasing **Eggs**	0,30	0,84	1,15
7	If purchasing **Eggs** and **Soy Sauce**, then purchasing **Cooking Oil**	0,30	0,81	1,23
8	If purchasing **Flour** and **Candy**, then purchasing **Eggs**	0,30	0,83	1,14
9	If purchasing **Flour** and **Candy**, then purchasing **Cooking Oil**	0,30	0,83	1,26
10	If purchasing **Cooking Oil** and **Candy**, then purchasing **Flour**	0,30	0,81	1,19
11	If purchasing **Eggs** and **Candy**, then purchasing **Flour**	0,30	0,79	1,17

According to Table 4, using 3 item sets forms 11 association rules, with the most frequently appearing items being cooking oil, eggs, flour, and candy. Therefore, the supermarket can recommend implementing sales strategies to enhance profitability by preparing a large quantity of the top 4 simultaneously purchased items, such as Cooking Cooking Oil, Eggs, Flour, and Candy. Apart from that, the association rules formed in Table 4 use the highest Support, namely a minimum of 45% and a minimum Confidence of 80%, which can recommend supermarkets to place Flour and Cooking Oil Oil next to Eggs to make it easier for customers to search for goods, thereby increasing sales. Not only that, the supermarket makes packages combining Flour, Cooking Oil and Eggs to support marketing strategies.

The association rules generated by the FP-Growth method for both 2-item- and 3-item sets reveal items frequently purchased by customers, consistently highlighting Cooking Oil, Eggs, Flour, and Candy. The findings of this research can serve as a benchmark for the supermarket in managing inventory and devising strategies to enhance sales for greater profitability. **The findings of this research** include utilizing the FP-Growth method for analyzing customer purchasing patterns in supermarkets, resulting in the extraction of 10 association rules for 2-item sets and 11 association rules for 3-item sets, based on a minimum Support of 30% and minimum Confidence of 70%. The selection of these threshold values for Support and Confidence is **supported by previous studies** [13, 25]. The use of different support values affects the number of association rules formed [26, 27]. A higher Support value tends to lead to fewer association rules being formed, as shown in Table 5 [28].

Table 5. The Number of Association Rules Formed Based on Support Value

Support	Confidence	Number of Association Rules	
		2 Itemset	3 Itemset
30%		10	11
40%	70%	6	3
50%		6	0
30%		2	10
40%	80%	2	3
50%		2	0

4. CONCLUSION

This research aims to analyze supermarket purchasing patterns using the FP-Growth method to understand customer buying behavior and identify relevant patterns from transaction data. Applying the FP-Growth method in analyzing customer purchasing patterns in supermarkets resulted in the extraction of 10 association rules for 2-item sets and 11 association rules for 3-item sets, based on a minimum Support of 30% and minimum Confidence of 70%. The association rules generated by the FP-Growth method for both 2-item sets and 3-item sets consistently highlighted items frequently purchased together, including Cooking Oil, Eggs, Flour, and Candy. The outcomes of this study can serve as a reference for supermarkets in managing inventory and formulating strategies to increase sales for greater profitability. Future research could explore customer segmentation based on purchasing patterns derived from association rules using a combination of clustering and association techniques.

5. DECLARATIONS

AUTHOR CONTIBUTION

The first author, Hairani, contributed to data processing, the model's development, and the paper's writing. In contrast, the second author, Juvenal Ximenes Guterres, contributed to the review of the paper's content.

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COMPETING INTEREST

The authors declare no competing interests regarding the data presented in this research.

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