

CONSUMER PURCHASING PATTERN ANALYSIS USING THE FP-GROWTH ALGORITHM TO SUPPORT BUSINESS DECISION-MAKING

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Abstract: Customer purchasing pattern analysis is an important aspect of improving marketing effectiveness and optimizing sales strategies. One approach that can be employed is Market Basket Analysis (MBA), which aims to identify relationships among products that are frequently purchased together. This study applies the FP-Growth algorithm to analyze customer purchasing patterns at CV Aksara IT Solution, a company engaged in computer equipment sales. The study aims to identify customer purchasing patterns and utilize these patterns to optimize marketing strategies, enhance cross-selling opportunities, and improve the customer shopping experience. The FP-Growth algorithm was selected due to its efficiency in identifying frequent itemsets without requiring candidate generation, as in the Apriori algorithm. The dataset consisted of 722 transaction records collected over a period of two years and three months. The analysis identified 17 association rules. The strongest association rule showed that customers who purchased a BNC Connector also purchased a CCTV RG59 Cable + Power, with a support of 78.6% and a confidence of 100%. Similarly, customers who purchased a DC Male Connector also purchased a CCTV RG59 Cable + Power, with a support of 76.6% and a confidence of 100%. Another significant pattern indicated that customers who purchased a DC Male Connector also purchased a BNC Connector, with a support of 76.6% and a confidence of 100%. These findings can support CV Aksara IT Solution in improving marketing strategies through strategic product placement, product bundling, promotional discounts, and data-driven recommendation systems. Therefore, the application of the FP-Growth algorithm in Market Basket Analysis can provide valuable insights into customer purchasing behavior and contribute to more effective sales and marketing strategies.

Keywords: Market Basket Analysis, FP-Growth, Purchasing Pattern

1. Introduction

The retail industry utilizes sales transaction data as an important source of information for understanding market conditions and customer behavior. Along with technological advancements, transaction data can be stored in databases connected to servers, enabling the data to be systematically managed and processed. The stored data can be transformed into various reports, such as sales reports and profit-and-loss reports. Through more in-depth analysis, transaction data can also generate new and valuable information that can support business decision-making. CV Aksara IT Solution is a business entity engaged in the sale of computer equipment.

CV Aksara IT Solution currently faces challenges in managing and utilizing its transaction data. The available transaction data has not been fully utilized and is primarily limited to monthly store sales reports, resulting in the accumulation of transaction data over time. In addition, inventory management remains a challenge, as some products frequently experience stock shortages, while others accumulate in inventory, potentially resulting in financial losses. Furthermore, product placement is still primarily organized according to product groups and categories. This approach does not sufficiently consider customer purchasing patterns due to the limited utilization of information derived from transaction data.

To address these issues, a web-based system is required to process transaction data and transform it into valuable information that can support business decision-making. This system utilizes data mining techniques. Data mining is a process of exploring databases to discover interesting patterns that can generate useful information for decision-making [1]. The main objective of data mining is to obtain valuable information that can be utilized to support organizational and business needs [2]. Therefore, this study aims to identify frequently purchased and highly demanded product combinations among customers. The study applies the *Market Basket Analysis* (MBA) method to identify association rules among combinations of items contained in transaction data and employs the FP-Growth algorithm to discover frequently occurring itemsets within a dataset [3]. The contribution of this research lies in the application of the FP-Growth algorithm at CV Aksara IT Solution to transform transaction data into actionable information that can be used to identify frequently purchased products and understand customer

purchasing patterns, particularly products that are commonly purchased together. This approach has not previously been implemented at the company.

Previous research has investigated the implementation of the FP-Growth algorithm by comparing the Apriori and FP-Growth algorithms in *Market Basket Analysis* to analyze purchasing patterns in bakery sales data. The study found that FP-Growth was able to generate association rules with higher confidence values. The dataset consisted of 20,508 transactions obtained from the Kaggle website and uploaded by Quila in 2022. The results showed that the highest confidence value generated by the Apriori algorithm was 54.06% for the association between *alfajores* and *coffee*, while the lowest confidence value was 33.86% for the association between *pastry* and *bread*. Meanwhile, FP-Growth produced a highest confidence value of 55.21% for the association between *pastry* and *coffee*, while the lowest confidence value was 33.86% for the association between *pastry* and *bread* [4]. These findings indicate differences in the association patterns generated by the Apriori and FP-Growth algorithms.

Another study analyzed purchasing patterns at Lathansa Café and Ramen using the FP-Growth algorithm with the assistance of RapidMiner. The study used 50 transaction records involving eight items. The resulting association rules achieved a support value of 32% and a confidence value of 94.1%. The highest-valued rule indicated that customers who purchased *vegetable martabak* also tended to purchase *economical package A* [5]. In another study, the FP-Growth algorithm was applied to investigate religious beliefs among university students using questionnaire data. The study collected 262 online questionnaires and 200 offline questionnaires, with a minimum support value of 0.1 and a minimum confidence value of 0.6. The resulting association rules achieved a confidence value of 83% and a support value of 31% in identifying relationships among students' religious beliefs, ethical considerations, and personal dilemmas and challenges [6].

Based on the discussion above, identifying association rules requires an *association rule mining* process within data mining to determine relationships that satisfy the minimum support and minimum confidence thresholds in a database [7]. *Association rule mining* is also commonly associated with *Market Basket Analysis* [8]. The objective of *Market Basket Analysis* is to identify products that customers tend to purchase simultaneously [9]. *Market Basket Analysis* generally employs three important parameters: *support*, *confidence*, and *lift ratio* [10]. The Apriori algorithm is one of the algorithms that can be used to implement *Market Basket Analysis*. However, Apriori has limitations because it requires repeated database scans and candidate generation, which can increase computational time, particularly when dealing with large datasets. An alternative approach is the FP-Growth algorithm, which addresses some of these limitations [11]. FP-Growth is an improvement over the Apriori approach and offers advantages in terms of processing efficiency because it constructs an FP-Tree to represent frequent patterns and reduces the need for repeated database scanning [12]. The FP-Growth algorithm is designed to identify frequently occurring itemsets (*frequent itemsets*) within a dataset [13].

2. Research Methods

The research framework is a systematic concept or structure that organizes the research flow, methods, and stages to achieve the intended objectives. It serves as a guideline for conducting the research, ensuring that the research process is structured and that appropriate solutions can be developed to address the problems under investigation. The research framework used in this study is presented in Figure 1.

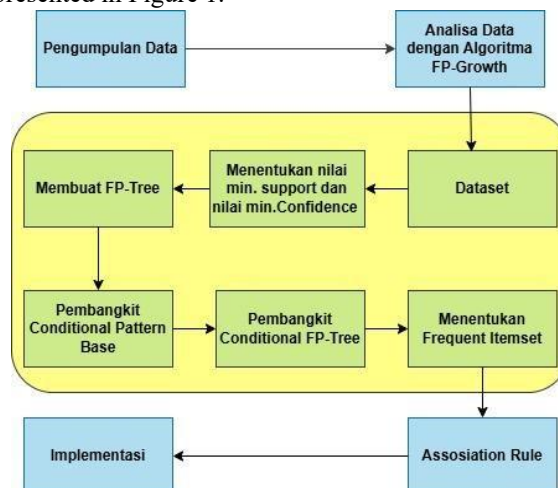


Figure 1. Research Framework

This data mining research involves several stages of analysis, including data collection, data analysis using the FP-Growth algorithm, association rule analysis, and implementation. The data analysis using FP-Growth consists of several steps, beginning with data collection and dataset analysis, followed by determining the support and confidence values, constructing the FP-Tree, generating the Conditional Pattern Base, constructing the Conditional FP-Tree, and finally identifying the frequent itemsets. The steps involved in the research framework are described as follows.

2.1 Data Collection

This stage involves obtaining data directly from the research site. The data consist of XLS spreadsheet files covering the period from January 2021 to March 2023. The collected data are then processed and analyzed to generate new and useful information.

2.2 Data Analysis Using the FP-Growth Algorithm

At this data analysis stage, the FP-Growth algorithm is used to manage and process sales transaction data based on the FP-Growth calculation procedure. The process begins by preparing the required dataset and determining the minimum support threshold, followed by constructing the FP-Tree.

Based on the results obtained, the Conditional Pattern Base and Conditional FP-Tree are then generated. Subsequently, frequent itemsets are identified based on the association rules. The resulting association rules are determined according to the predefined minimum support and minimum confidence thresholds.

2.3 Dataset

At the dataset processing stage, the data used in this study were obtained from the conversion of the original transaction data. The dataset consists of sales transactions collected over a period of two years and three months. After the selection and preprocessing process, a total of 98 transactions were obtained. The selected and transformed data were then used as the basis for the subsequent stages of analysis.

2.3.1 Determining the Minimum Support and Minimum Confidence Values

In this study, the support values obtained from the initial analysis were used as the basis for the subsequent stage. At this stage, the researcher determined a minimum support threshold of 60% and a minimum confidence threshold of 80%. The support value for each item was calculated based on the available reference [15].

$$\text{Support}(A) = \frac{\sum \text{Transaksi yang mengandung } A}{\sum \text{Transaksi}}$$

After calculating the support values, the frequency with which specific combinations of items appear in the sales transaction data can be determined. The analysis of sales data can reveal significant patterns and relationships among purchased items. The support value for a combination of items is calculated using the following formula [15]:

$$\text{Support}(A, B) = \frac{\sum \text{Transaksi yang mengandung } A, B}{\sum \text{Transaksi}} \times 100\%$$

After determining the support value, the analysis proceeds to another important measure, namely confidence. Confidence plays an important role in analyzing the relationship between items. It is used to determine how frequently an association rule is valid or holds true within the sales transaction data. The confidence value is calculated using the following formula [15]:

$$\text{Confidence}(A, B) = \frac{\sum \text{Transaksi yang mengandung } A \text{ dan } B}{\sum \text{Transaksi } A} \times 100\%$$

2.3.2 Creating an FP-Tree

The steps involved in creating this FP-tree include a transaction flow based on the previously sorted elements. Each transaction is divided into several elements, which are then linked according to the order of the elements, forming an efficient tree structure for further analysis. The result of this process is an FP-tree representing 98 transactions.

2.3.3 Conditional Pattern Base Generator

The conditional FP-Tree generation stage aims to develop results that align with the conditional pattern base. This step plays a crucial role in identifying more specific element frequency patterns. In this stage, each element in the FP-Tree is analyzed in greater depth to form

a subtree that represents patterns associated with that element. The results from the conditional FP-Tree will then be used to formulate more specific and meaningful association rules.

2.3.4 Creating Frequent Itemsets

The frequent itemset stage aims to combine items from each conditional FP-Tree result, which is useful for forming the resulting frequency patterns. This process identifies items that frequently appear together in sales transaction data to uncover strong associations between items. By using frequent itemsets, significant relationships between itemsets can be analyzed in greater depth, enabling the development of rules that support the formulation of sales strategies and subsequent business decision-making.

2.4 Association Rule

After obtaining the frequent item sets, the next step is to identify association rules. These rules are derived based on the minimum support and confidence thresholds that were previously established. By setting these support and confidence thresholds, less relevant rules are filtered out, allowing the analysis to focus on patterns that can provide valuable insights.

2.5 Implementation

This stage involves the implementation process, in which calculations are performed to increase future sales of goods using the FP-Growth algorithm manually. This implementation consists of applying the identified association rules to design more effective and efficient marketing strategies, complete with even more optimal product offerings.

3. Results and Discussion

The data used in this study consists of sales figures from January 2021 through March 2023, covering a period of 2 years and 3 months. The data obtained will then be analyzed to formulate strategies for increasing sales. Data processing was performed by applying the FP-Growth algorithm using Microsoft Excel. For more details, see the data analysis flowchart in Figure 2.



Figure 2. Data Analysis Workflow

A total of 722 data points were used. In this stage of the analysis process, the data processed consisted of collected sales transaction data; the data was then analyzed using the FP-Growth algorithm until the results—in the form of analyzed data—were obtained.

3.1 Dataset

The dataset used consists of data that has been transformed into binary values. The transformed data was obtained from a selection of sales data spanning 2 years and 3 months, totaling 98 transactions, based on individual transactions. Among these 98 transactions, there are 30 itemsets, each labeled with the symbol “K.” The dataset is shown in Table 1.

Table 1. Dataset

Tran saksi	1	2	3	4	5	6	7	8	9	10		98
K1	1	1	0	1	1	0	1	0	0	1		0
K2	1	0	1	1	1	0	0	1	1	1		1
K3	1	1	1	1	1	1	1	1	1	1		1
K4	1	0	1	0	1	1	1	0	0	0		0
K5	0	0	0	1	0	1	1	0	1	1		1
K6	0	1	0	1	0	0	1	1	0	1		1
K7	0	1	1	0	1	0	1	1	0	1		1
K8	1	1	0	1	1	1	1	1	1	0		1
K9	1	1	1	1	1	1	1	1	1	1		0
K10	1	1	0	1	1	1	1	1	1	1		1
....	...	...	...	...	...	...	...	...	...	...		...
K28	1	1	1	1	1	1	1	1	1	0		1
K29	1	1	1	1	0	0	0	0	0	0		0
K30	1	1	1	1	1	1	1	1	1	1		1

The dataset used consists of repeated transaction data for 30 items, labeled K1 through K30. Each row represents an

item, and each column represents a sales transaction. The values 0 and 1 have the following meanings: a value of 1 indicates that the item was purchased during a specific transaction, while a value of 0 indicates the opposite.

3.2 Determining the Minimum Support Value and the Minimum Confidence Value

The minimum support value was set at 60%, while the confidence level was set at 80%. Based on these values, the results of the association rules were obtained, which can be used to help businesses understand consumer purchasing behavior patterns. The table below presents the support values for each item set identified, as shown in Table 2.

Table 2. Calculation of Support Values

Item	Frekuensi	Nilai Support	Nilai Support %
K4	77	$77/98 = 0,7857$	78,57%
K7	77	0,7857	78,57%
K8	76	0,7653	76,53%
K6	71	0,7245	72,45%
K5	69	0,7041	70,41%
K25	67	0,6837	68,37%
K15	59	0,6020	60,20%

Based on the support calculations, it can be concluded that there are seven items that appear frequently with a minimum support threshold above 60%: K4, K7, K8, K6, K5, K25, and K15. The next step is to sort the dataset by priority, as shown in Table 3 below.

Table 3. Dataset sorted by priority

TID	Itemset
1	K4, K7, K8, K6, K5, K25
2	K4, K7, K8, K6, K25
3	K4, K7, K8, K6, K5, K25
4	K4, K7, K8, K6, K5, K25, K15
5	K4, K7, K8, K6, K5, K25
6	K4, K7, K8, K6, K5, K25
7	K4, K7, K8, K6, K5, K25
8	K4, K7, K8, K6, K5, K25
9	K4, K7, K8, K6, K5, K25
10	K4, K7, K8, K6, K5, K25, K15
.....	
98	K4, K7

The dataset shown in Table 3 above displays various items associated with specific transactions and identified by their TID (Transaction ID). Each itemset consists of a unique combination of items. This dataset is used to detect item or product frequency patterns, and it also reveals the relationships between products in each transaction.

3.3 Creating an FP-Tree

At this stage, based on the previously sorted items, the next step is to construct an FP-Tree. This stage creates a single FP-Tree representing 98 transactions. The construction of the FP-Tree begins with TID 1 (the first transaction) and continues through TID 98 (the last transaction). The final result of the FP-Tree after processing all 98 transactions is shown in Figure 3.

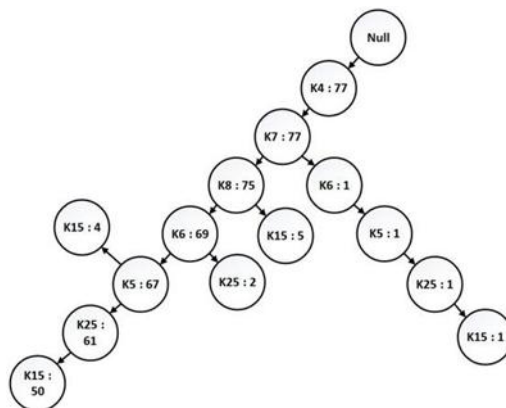


Figure 3. FP-Tree

The FP-Tree diagram, constructed from TID1 to TID98, shows a tree structure that illustrates the frequency patterns of items in the sales transaction data. Each node in the FP-Tree represents an item, while its branches indicate frequently occurring transaction paths. This FP-Tree makes it easier to identify sets of items that frequently appear together and helps in understanding the relationships between individual items and those found across all transactions.

3.4 Conditional Pattern Base Generator

In this Conditional Pattern Base, path patterns are created based on item sets so that they correspond to the items being analyzed. One such path pattern is the K25 item path pattern shown in Figure 4 below.

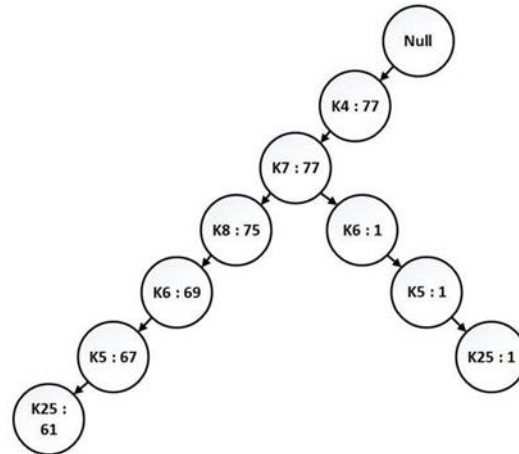


Figure 4. Paths containing the K25 item suffix

Figure 4 above shows a path that ends with item K25. The K25 path illustrates how an item is connected to other items in the preceding Fp-Tree. This flow analysis shows that it is possible to identify groups of important items that can serve as the focus of marketing strategies.

3.5 Conditional FP-Tree Generator

Building a Conditional FP-Tree. This process is carried out by referencing and adjusting the data in the Conditional Pattern Base. The results of the Conditional FP-Tree are shown in Table 4.

Table 4. Conditional FP-Tree

Item	Conditional FP-Tree
K15	{K4, K7 : 60} {K8, : 59} {K6, K5 : 55} {K25 : 51}
K25	{K4, K7, K6 : 64} {K8, : 63} {K5 : 62}
K5	{K4, K7, K6 : 68} {K8, : 67}
K6	{K4, K7 : 70} {K8, : 69}
K8	{K4, K7 : 75}
K7	{K4, K7 : 77}

Table 4 above presents the Conditional Fp-Tree for various items and shows the item selection patterns for a specific transaction. Each row indicates how often an item appears together with other items. For example, K15 frequently appears together with items K4, K7, K8, K6, K5, and K25 in 55 transactions.

3.6 Identifying Frequent Itemsets

After obtaining the Conditional FP-Tree, the next step is to identify the frequent itemsets. The frequent itemsets are shown in Table 5 below.

Table 5. Frequent Itemsets

Item	Frequent Itemset
K15	{K4, K7, K15} {K8, K15} {K6, K5, K15} {K25, K15}
K25	{K4, K7, K6, K25} {K8, K25} {K5, K25}
K5	{K4, K7, K6, K25 } {K8, K25}
K6	{K4, K7, K6} {K8, K6}
K8	{K4, K7, K8}
K7	{K4, K7}

Table 5 above presents a general collection of items derived from various different items and shows combinations of items that frequently appear together in transactions. Each row in the table represents a specific item association pattern, such as K15 or K7, which frequently appear together with various other items in a number of transactions, thereby forming a strong frequent itemset. Frequent itemset analysis plays a crucial role in identifying significant patterns in sales transaction data, which can then be used to formulate correlation rules to support business strategies.

3.7 Association Rule

The final step in the FP-Growth algorithm is to determine the association rules. Once the frequent itemsets have been successfully identified, the next step is to generate association rules based on combinations of two items. The combinations of two items used to calculate the association rules are shown in Table 6 below.

Table 6. Association Rules Derived

Kombinasi 2 Itemset	Frekuensi	Support	Confidence
K7, K4	77	78,6%	100%
K8, K4	75	76,5%	100%
K8, K7	75	76,5%	100%
K6, K4	71	72,4%	100%
K6, K7	71	72,4%	100%
K6, K8	69	70,4%	97,2%
K5, K4	69	70,4%	100%
K5, K7	69	70,4%	100%
K5, K6	69	70,4%	100%
K5, K8	68	69,4%	98,6%
K25, K4	67	68,4%	100%
K25, K7	67	68,4%	100%
K25, K6	67	68,4%	100%
K25, K8	66	67,3%	98,5%
K25, K5	66	67,3%	98,5%
K15, K4	59	60,2%	100%
K15, K7	59	60,2%	100%
K15, K8	58	59,2%	98,3%
K15, K6	54	55,1%	91,5%
K15, K5	54	55,1%	91,5%
K15, K25	51	52%	86,4%

Table 6 above shows the results of the calculations, from which it can be concluded that there are 17 item combinations that meet the criteria for minimum support and minimum confidence. The following are the 10 insights obtained and listed:

1. The combination K7 => K4 shows a support value of 78.6% and a confidence value of 100%, which means that "If consumers buy a BNC connector, they will also buy RG59 CCTV cable + power."
2. The combination K8 => K4 shows a support value of 76.5% and a confidence value of 100%, which means that "If a customer buys a DC Male Connector, they will also buy RG59 CCTV Cable + Power."
3. The combination K8 => K7 shows a support value of 76.5% and a confidence value of 100%, which means that "If a customer buys a DC Male Connector, they will also buy a BNC Connector."
4. The combination of K6 => K4 shows a support value of 72.4% and a confidence value of 100%, which means that "If a customer buys a 10A Mains PSU, they will also buy an RG59 CCTV Cable + Power."
5. The combination K6 => K7 shows a support value of 72.4% and a confidence value of 100%, which means that "If a customer buys a 10A mains PSU, they will also buy a BNC connector."
6. The combination K6 => K8 shows a support value of 70.4% and a confidence value of 97.2%, which means that "If a customer buys a 10A mains PSU, they will also buy a male DC connector."

7. The K5 => K4 combination indicates a support value of 70.4% and a confidence value of 100%, which means that “If a customer buys a 1.5M Micro Kingdom HDMI cable, they will also buy an RG59 CCTV cable with power.”
8. The combination of K5 => K7 shows a support value of 70.4% and a confidence value of 100%, which means that “If a customer buys a 1.5M Micro Kingdom HDMI cable, they will also buy a BNC connector.”

4. Conclusion

The conclusion of this study is that the application of the FP-Growth algorithm plays a crucial role in analyzing sales data to improve marketing strategies at CV Aksara It Solution. By analyzing 98 transactions over a period of two years and three months, this study successfully identified 17 two-item combinations with a minimum support of 60% and a confidence level of 80%. The purchasing patterns identified—such as items K4, K7, and K8, which appear in every transaction—provide valuable insights for the company in designing more effective sales strategies.

This study also demonstrates that the FP-Growth algorithm helps the company extract new and important information from large and complex sales data. By using this data mining technique, the company can optimize inventory management, reduce the risk of inventory buildup, and respond more quickly to changes in consumer trends. Therefore, the implementation of the FP-Growth algorithm at CV Akasara It Solution can serve as an effective and efficient model for other companies in managing sales data to improve profitability and operational efficiency.

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