

## Analysis Of Motorcycle Spareparts Purchase Patterns At Boang Moto Shop Using The Fp Growth Method To Support Business Strategy

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### ABSTRACT

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The current development of the automotive industry increases the need for after-sales services for motor vehicles, including the provision of spare parts. Boang Moto Shop, as an automotive MSME, faces challenges in stock management due to the suboptimal utilization of available sales transaction data. This study aims to analyze consumer purchasing patterns to find combinations of spare parts that are frequently purchased together. The method used is data mining by applying the Frequent Pattern Growth (FP-Growth) algorithm. Data processing is carried out through the RapidMiner application using sales transaction data for three months. The analysis process starts from the data preprocessing stage, FP-Tree formation, to the extraction of association rules based on support, confidence, and lift ratio parameters. The results of this study are expected to provide recommendations for Boang Moto Shop management in the form of product package preparation (bundling), store layout arrangement, and determining inventory procurement priorities more effectively and efficiently to minimize the risk of stockpiling or running out of spare parts.

**Keyword :** *FP-growth, Data Mining, purchasing patterns, Association Analysis*



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### 1. INTRODUCTION

The automotive industry in Indonesia continues to grow, as evidenced by the annual increase in the number of motorized vehicles. This has led to a growing demand for vehicle maintenance services and spare parts. Motorcycle repair shops and spare parts stores play a crucial role in meeting these needs by providing a variety of vehicle components needed by consumers. The growth of the automotive industry also presents challenges in inventory management and customer service [1]. There is often a mismatch between stock availability and consumer needs, resulting in late service and reduced customer satisfaction [2].

Boang Moto Shop is one of the businesses engaged in motorcycle spare part sales. In its operational activities, this business generates sales transaction data that continues to increase every day. Unfortunately, the data is generally only used as transaction records and has not been optimally utilized as a source of information to support business decision-making. In fact, transaction data contains valuable information about customer purchasing behavior that can be used to improve the effectiveness of marketing strategies, inventory management, and customer service [3].

One of the problems often faced by motorcycle spare part stores is the difficulty in determining which products should be prioritized and provided in larger quantities. In addition, business owners do not yet have accurate information about the relationships between products that are frequently purchased together by customers. As a result, opportunities to implement marketing strategies such as product bundling and cross-selling are not utilized effectively. This condition shows the need for the use of information technology that can process transaction data into valuable information to support business development [4].

Data mining is one of the technologies that can be used to extract valuable information and hidden knowledge from large amounts of data. Data mining allows organizations or businesses to discover patterns, relationships, and trends that were previously unknown, which can then be used as a basis for decision-making. In the business field, data mining is widely applied to analyze customer behavior, optimize marketing strategies, and improve the operational efficiency of companies [5].

One of the techniques widely used in data mining is Association Rule Mining. Association Rule Mining is a data mining technique used to discover relationships between products that are frequently purchased together in a single transaction. This pattern information can be utilized by businesses to develop appropriate marketing strategies, manage inventory, and increase sales through related product recommendations [6].

The FP-Growth (Frequent Pattern Growth) algorithm is an Association Rule Mining method that is highly efficient for discovering frequent itemsets in large and complex sales transaction datasets. This algorithm improves on Apriori by eliminating repeated candidate generation. With the FP-Tree (Frequent Pattern Tree) data structure, the number of database scans is reduced, making the analysis process much faster and more efficient [7].

## 2. RESEARCH METHOD

This research uses the KDD (Knowledge Discovery in Databases) approach, which is a structured method used to assist the data mining process [8] discover hidden patterns, information, and knowledge from large data sets. The research data comes from transactions at the Boang Moto Shop. KDD is often equated with data mining, but data mining is only one of the stages of KDD. The research stages include five main processes: data selection, preprocessing, data transformation, data mining, and evaluation.

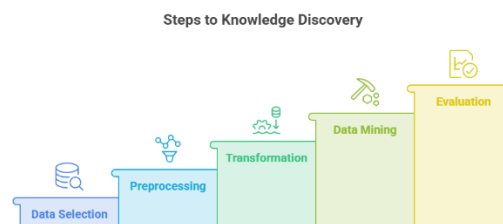


**Figure 1. Knowledge Discovery in Databases (KDD) Process**

The first stage of KDD is data selection. In this stage, researchers identify and collect relevant data sources, then select a subset of the data from the primary database [9]. This step is crucial for narrowing the analysis area and reducing the computational burden, allowing for more focused and efficient subsequent processing.

After data selection, the next step is preprocessing. This stage cleans, normalizes, and prepares the data for processing [10]. Raw data often contains noise, duplication, inconsistent formats, and missing values. In the preprocessing stage, researchers correct these issues to ensure the data is valid and does not compromise the accuracy of subsequent analysis.

The cleaned data proceeds to the data transformation stage. Data transformation converts the data into a format suitable for the research process [11]. Activities at this stage include normalization (adjusting the numerical scale), aggregation (summarizing the data), and dimensionality reduction to simplify complex variables for processing.

Once the data is prepared in the correct format, the next step is the data mining process. Data mining techniques are used to discover relationships between various items in the dataset. These relationships are represented as association rules that indicate which items are frequently purchased or appear together [12]. The final stage of this method is Evaluation or Interpretation. In this stage, the patterns or models found during the data mining process are checked to make sure they are valid and accurate before they are used.

The final stage of this method is evaluation. The patterns or mathematical models generated from the data mining process are not used immediately but must first be tested for validity and accuracy using specific metrics. After going through the evaluation process, the resulting patterns are then interpreted into more understandable information, such as visualizations or data representations, so that they can produce new useful knowledge that can be applied in business strategies and decision-making [13].

### 3. RESULTS AND DISCUSSION

In this section, this study utilizes data on motorcycle spare part sales transactions, and stock management is the process of managing inventory to maintain the availability of goods in accordance with operational needs and customer demand. [14]. The data was obtained directly from Boang Moto Shop over a period of 3 months, from October to December. The collected raw data from daily transaction records was initially processed through a cleaning process to remove noise, duplicate data, recording errors, or missing values in order to ensure validity of the actual results. Through the data selection process, the analysis focus was narrowed down to the main spare part product items, namely roller, double clutch pad, roller house, V-belt, engine oil, axle oil, carburetor cleaner, griss, injection infusion fluid, and slide piece.

**Table 1. Transaction Data**

| Customer | Roller | Double Canvas | Roller House | V-belt | Engine Oil | Axle Oil | Carbu Cleaner | Griss | Infusion Injection Fluid | Slide Piece |
|----------|--------|---------------|--------------|--------|------------|----------|---------------|-------|--------------------------|-------------|
| 1        | 1      | 1             | 0            | 0      | 1          | 1        | 1             | 1     | 1                        | 0           |
| 2        | 0      | 1             | 0            | 0      | 1          | 0        | 0             | 0     | 0                        | 0           |
| 3        | 0      | 0             | 0            | 1      | 1          | 0        | 0             | 0     | 0                        | 0           |
| 4        | 1      | 0             | 1            | 0      | 0          | 0        | 1             | 1     | 0                        | 1           |
| 5        | 0      | 0             | 0            | 0      | 1          | 1        | 0             | 0     | 0                        | 1           |
| 6        | 0      | 0             | 0            | 0      | 0          | 0        | 1             | 0     | 0                        | 1           |
| 7        | 0      | 0             | 0            | 0      | 1          | 1        | 1             | 0     | 1                        | 0           |
| 8        | 1      | 1             | 1            | 1      | 1          | 1        | 1             | 1     | 1                        | 1           |
| 9        | 0      | 0             | 0            | 0      | 1          | 1        | 0             | 0     | 0                        | 0           |
| ...      | ...    | ...           | ...          | ...    | ...        | ...      | ...           | ...   | ...                      | ...         |
| 72       | 0      | 0             | 0            | 0      | 1          | 1        | 0             | 0     | 0                        | 0           |
| 73       | 1      | 0             | 0            | 0      | 0          | 0        | 0             | 0     | 0                        | 0           |
| 74       | 0      | 0             | 0            | 0      | 1          | 1        | 1             | 1     | 1                        | 0           |
| 75       | 0      | 0             | 0            | 0      | 1          | 0        | 0             | 0     | 0                        | 1           |

Binomial binary is a crucial step in data mining before the data is fed into the FP-Growth algorithm. The main goal of this stage is to convert raw transaction data (which is usually a list of items per note) into binary form (0 and 1) so that computers and software like RapidMiner can quickly calculate support and confidence values.

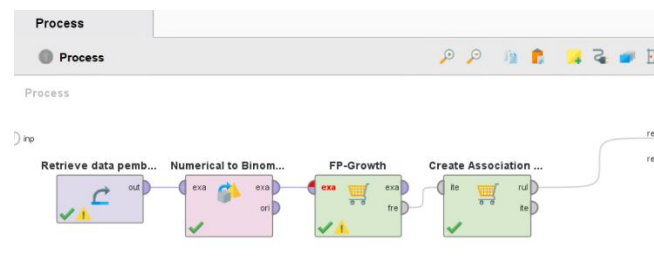


**Figure 2. RapidMiner (AI Studio)**

After the data has been successfully loaded into the system, the next step is to connect the data flow to the Numerical to Binominal operator. The use of this operator aims to convert the data type that was originally in numerical form into categorical data in a binary format (true/false).

Retrieve FP-Growth Purchase Data (Raw Data Retrieval Process): Retrieve Data refers to the process of collecting or retrieving related data [15], This step is important to ensure the quality and integrity of the data before the processing stage begins. The data processing flow in the AI Studio software starts with the implementation of the first operator, which functions to retrieve and load the transaction record files containing the purchase history of spare parts from Boang Moto Shop stored in the local computer repository. After the entire dataset has been successfully identified and uploaded into the system, the data flow is then digitally transmitted through the output (out) port as a connection bridge that forwards the data package to the next stage.

Numeric to Binominal Transformation (Binary Matrix Transformation): This preprocessing step converts numerical data into binary values (0 and 1) so the transaction data can be processed using the FP-Growth algorithm. The transformation shows whether an item is present or absent in each transaction, making it easier to identify relationships and purchasing patterns between items [16]. This step is necessary because the FP-Growth algorithm in AI Studio only works with binominal data. In the transformed data, a value of 1 means the spare part was purchased in a transaction, while a value of 0 means it was not purchased.

FP-Growth (Frequent Itemset Discovery): The frequent itemset discovery stage focuses on determining whether the conditional FP-Growth is a single path. The output generated is a set of frequent itemsets by combining each item with every conditional FP-Growth. Meanwhile, if the conditional FP-Growth is not a single path, the FP-Growth process needs to be performed recursively [17]. This algorithm works by scanning the entire transaction database to compress purchase records into a special data structure called a Frequent Pattern Tree (FP-Tree). The pattern discovery process using the FP-Growth algorithm utilizes the FP-Tree structure, which functions to store and organize transaction data based on the frequency of item occurrences.

Unlike other association rule discovery methods, FP-Growth extracts frequent itemsets directly from the FP-Tree structure through several stages, including the formation of the conditional pattern base, the construction of the conditional FP-Tree, and the discovery of frequent itemsets. Item combinations that have occurrence frequencies matching the predetermined minimum support value are selected as patterns that meet the criteria for further analysis [18].

The product combinations (frequent itemsets) identified in the previous phase are then explored further using the Create Association Rules operator. In accordance with the methodology, this step is carried out to generate association rules that represent the relationships between spare parts based on customer purchasing behavior. Through this process, the system calculates the confidence value to measure the probability that the purchase of one product leads to the purchase of its complementary product within the same transaction. In addition, the lift ratio value is used to see whether the relationship between items is truly meaningful or just occurs by chance. Association rules that meet the

minimum confidence and lift ratio thresholds will be adopted as the final conclusions of the research [19]. High confidence and lift ratio values become the main indicators that the relationship between products in customer purchasing patterns is very strong and valid.

**Table 2. Association Rules**

| No. | Premises                         | Conclusion                | Support | Confidence | LaPlace | Gain  | p-s   | Lift  |
|-----|----------------------------------|---------------------------|---------|------------|---------|-------|-------|-------|
| 2   | Axle Oil                         | Engine Oil                | 0.400   | 1          | 1       | 0.400 | 0.228 | 2.327 |
| 3   | Engine Oil, Griss                | Carbu Cleaner             | 0.200   | 1          | 1       | 0.200 | 0.109 | 2.208 |
| 4   | Engine Oil, Carbu Cleaner        | Axle Oil                  | 0.227   | 1          | 1       | 0.227 | 0.136 | 2.500 |
| 5   | Carbu Cleaner, Axle Oil          | Engine Oil                | 0.227   | 1          | 1       | 0.227 | 0.129 | 2.327 |
| 6   | Engine Oil, Griss                | Axle Oil                  | 0.200   | 1          | 1       | 0.200 | 0.120 | 2.500 |
| 7   | Griss, Axle Oil                  | Engine Oil                | 0.200   | 1          | 1       | 0.200 | 0.114 | 2.327 |
| 8   | Griss, Axle Oil                  | Carbu Cleaner             | 0.200   | 1          | 1       | 0.200 | 0.109 | 2.208 |
| 9   | Griss, Injector Infusion Fluid   | Carbu Cleaner             | 0.240   | 1          | 1       | 0.240 | 0.131 | 2.208 |
| 10  | Engine Oil, Griss                | Carbu Cleaner, Axle Oil   | 0.200   | 1          | 1       | 0.200 | 0.155 | 4.412 |
| 11  | Engine Oil, Carbu Cleaner, Griss | Axle Oil                  | 0.200   | 1          | 1       | 0.200 | 0.120 | 2.500 |
| 12  | Griss, Axle Oil                  | Engine Oil, Carbu Cleaner | 0.200   | 1          | 1       | 0.200 | 0.155 | 4.412 |
| 13  | Engine Oil, Griss, Axle Oil      | Carbu Cleaner             | 0.200   | 1          | 1       | 0.200 | 0.109 | 2.208 |
| 14  | Carbu Cleaner, Griss, Axle Oil   | Engine Oil                | 0.200   | 1          | 1       | 0.200 | 0.114 | 2.327 |

The analysis results table comprehensively displays a visualization of the association rule matrix that represents the patterns of association and relationships between spare parts products that are frequently purchased together by customers. In association rule analysis, each rule has a premises section as the initial conditions or combination of items that appear in a transaction, while the conclusion section shows other items that are related based on the probability value of joint purchases. This approach is used to discover consumer purchasing patterns and support decision-making in spare parts inventory management using the FP-Growth algorithm [20].

to ensure the validity and accuracy of Association Rules, is one of the data mining approaches that can be used to find item associative rules. These association rules are created by identifying the most significant relationships from frequently occurring data patterns using support and confidence parameters [21]. Meanwhile, the confidence parameter provides an overview of the degree of certainty or predictive confidence level that a customer who has entered a product in the premises section into the shopping cart [21], will certainly also redeem the product listed in the conclusion section in the same payment note.

#### Example of Association Rule Calculation (Axle Oil - Engine Oil)

##### Support

The support value in the table for this rule is **0.400**. If it is assumed that the total research data consists of **75 transactions** (based on the binary matrix draft):

$$Support(Axle\ Oil \rightarrow Engine\ Oil) = \frac{30}{75} = 0,40 = 40\%$$

This means that there are **30 transactions out of a total of 75 transactions** that contain both **Axle Oil** and **Engine Oil** products simultaneously in the same receipt.

##### Confidence

The confidence value in the table for this rule is **1 or 100%**:

$$Confidence(Axle\ Oil \rightarrow Engine\ Oil) = \frac{30}{30} = 1,0 = 100\%$$

This means that the confidence level of this rule is absolute; every time a customer purchases **Axle Oil**, it can be confirmed with **100% certainty** that the customer will also purchase **Engine Oil**.

##### Lift Ratio

The lift value in the table for this rule is 2.027:

$$Lift\ Ratio(Axle\ Oil \rightarrow Engine\ Oil) = \frac{Confidence}{Support\ Engine\ Oil} = 2.327$$

This means that because the lift ratio value is greater than one ( $> 1$ ), the relationship between **Axle Oil** and **Engine Oil** is proven to be valid, positive, and co-occurrence pattern on customer purchasing patterns (not occurring by chance).

#### Calculation of All Association Results

**Table 3. Association Rule Calculation Table**

| No. | Association Rules (X → Y)                                    | Support Calculation  | Confidence Calculation | Lift Ratio Calculation | Relationship status     |
|-----|--------------------------------------------------------------|----------------------|------------------------|------------------------|-------------------------|
| 2   | Axle Oil → Engine Oil                                        | 30/75 = <b>40%</b>   | 30/30 = <b>100%</b>    | 1,0 / 0,493 = 2,327    | Valid / Strong Positive |
| 3   | Engine Oil, Griss → Carbu Cleaner                            | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,453 = 2,208    | Valid / Strong Positive |
| 4   | Engine Oil, Carbu Cleaner → Axle Oil                         | 17/75 = <b>22,7%</b> | 17/17 = <b>100%</b>    | 1,0 / 0,400 = 2,500    | Valid / Strong Positive |
| 5   | Carbu Cleaner, Axle Oil → Engine Oil                         | 17/75 = <b>22,7%</b> | 17/17 = <b>100%</b>    | 1,0 / 0,493 = 2,027    | Valid / Strong Positive |
| 6   | Engine Oil, Griss → Axle Oli                                 | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,400 = 2,500    | Valid / Strong Positive |
| 7   | Griss, → Axle Oil                                            | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,493 = 2,027    | Valid / Strong Positive |
| 8   | Griss, Axle Oil → Carbu Cleaner                              | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,453 = 2,206    | Valid / Strong Positive |
| 9   | Griss, Injector Infusion Fluid → Carbu Cleaner               | 18/75 = <b>24%</b>   | 18/18 = <b>100%</b>    | 1,0 / 0,453 = 2,206    | Valid / Strong Positive |
| 10  | Engine Oil, Griss → Carbu Cleaner, Axle Oil                  | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,227 = 4,412    | Very strong             |
| 11  | Engine Oil, Carbu Cleaner, Griss → Axle Oil                  | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,400 = 2,500    | Valid / Strong Positive |
| 12  | Griss, Axle Oil Axle Oil Axle Oil → Engine Oil Carbu Cleaner | 15/75 = <b>20%</b>   | 15/15 = <b>100%</b>    | 1,0 / 0,227 = 4,412    | Very strong             |

Based on the data mining analysis results presented in the calculation table, the association rule **Engine Oil, Griss → Carbu Cleaner, Axle Oil** (Rule 10), as well as the rule **Griss, Axle Oil → Engine Oil, Carbu Cleaner** (Rule 12) has the same highest *lift ratio* value of 4.412. This indicates that This indicates a very strong relationship, showing that customers who decide to purchase the combination of spare parts in the **premises** (antecedent condition) have a tendency or probability **4.412 times higher** to also purchase the commodity package in the **conclusion** (consequence) compared to ordinary customers in general. Both rules are also supported by an absolute confidence value of **100%**, which indicates that the certainty level of these combined transactions is very high.

Furthermore, a single rule such as **Axle Oil → Engine Oil (Rule 2)** also demonstrates a highly significant and dominant purchasing relationship, with the highest support value among the other rules, reaching **40%**, a confidence value of **100%**, and a lift ratio index of **2.027**. These empirical findings indicate that both types of lubricants have a strong interrelated maintenance need for motorcycles in the eyes of

consumers. Therefore, these commodities have very high strategic potential to be optimized by the management of **Boang Moto Shop** through the implementation of periodic service product bundling strategies or the arrangement of display shelf layouts (cross-selling) by placing related products close to each other to stimulate sales volume.

Meanwhile, several other product package combinations, such as **Rule 4 (Engine Oil, Carbu Cleaner → Axle Oil)**, **Rule 6 (Engine Oil, Griss → Axle Oil)**, and **Rule 11 (Engine Oil, Carbu Cleaner, Griss → Axle Oil)**, consistently demonstrate a valid and strongly positive relationship, with a **lift ratio value of 2.500**. The overall pattern findings with lift values far exceeding one ( $>1$ ) in this table prove that the relationships between motorcycle spare parts formed at **Boang Moto Shop** occur purely due to real demand patterns from consumer purchasing habits, rather than coincidence or random events (**independent events**). All valid and highly strong association rule results are highly recommended to be adopted as a scientific basis for developing promotional programs and managing inventory control strategies.

#### 4. CONCLUSION

Based on the data mining analysis conducted using the Knowledge Discovery in Databases (KDD) framework, the FP-Growth algorithm successfully identified purchasing patterns among motorcycle spare parts at Boang Moto Shop across the analyzed three-month transaction dataset. The empirical evaluation revealed key associative rules.

1. Multi-item association rules, such as Engine Oil, Grease → Carburetor Cleaner, Axle Oil (Rule 10) and Grease, Axle Oil → Engine Oil, Carburetor Cleaner (Rule 12), demonstrated the highest lift ratio index of 4.412 with 100% confidence within the sample dataset, highlighting strong co-purchasing tendencies among routine maintenance products.

2. The single paired association *Axle Oil → Engine Oil* (Rule 2) exhibited the highest support value at 40.0% with a lift ratio of 2.027, confirming that these two lubricants frequently co-occur in single consumer transactions.

The transaction data from October to December showed several spare part combinations with strong purchase relationships. The association rules **Engine Oil, Grease → Carburetor Cleaner** and **Axle Oil → Engine Oil, Carburetor Cleaner** had the highest lift ratio of **4.412** with **100%** confidence, indicating that these combinations can be used as a sales strategy. In addition, the rule **Axle Oil → Engine Oil** had the highest support of **40%**, **100%** confidence, and a lift ratio of **2.027**, showing that these two products were the most frequently purchased together by customers at Boang Moto Shop.

Based on the research results, the FP-Growth algorithm has been proven to help Boang Moto Shop identify previously unseen customer purchasing patterns. This can be used to improve business strategies, such as creating product packages, arranging spare parts layouts based on purchasing patterns, and managing inventory to ensure the most frequently purchased products are always available.

For further research, the amount of transaction data can be increased and the observation period extended to allow for more diverse patterns and a more representative picture of the actual situation. Future research could also utilize other data mining methods or combine the FP-Growth algorithm with predictive techniques. The results not only demonstrate purchasing patterns but also provide more practical recommendations to aid inventory management and business strategy development.

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