

Association Rule Mining with FP-Growth for Cross-Selling Recommendation in a Culinary MSME

Bagas Ramadhan¹, Rudolf Januar², Firman Noor Hasan^{3*}

^{1,3} Informatics Engineering, Faculty of Industrial Technology and Informatics, Universitas Muhammadiyah Prof. Dr. Hamka, Jakarta, Indonesia

² Electrical Engineering, Special Program, Saints John's University, New Taipei City, Taiwan

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ABSTRACT

The rapid growth of digitalization in Micro, Small, and Medium Enterprises (MSMEs) has led to a significant increase in daily sales transaction data. However, most culinary MSMEs utilize this data merely as transaction records rather than processing it into valuable insights for business decision-making. Kedai Mie Rahma faces challenges in determining promotional strategies, designing menu packages, and managing raw material inventories due to the lack of systematic analysis of customer purchasing patterns. This study aims to extract valid association rules from sales data using the FP-Growth algorithm to provide data-driven cross-selling recommendations. The methodology follows the Knowledge Discovery in Databases (KDD) framework, analyzing 2,500 historical transactions from the Point of Sales (POS) system. The results successfully identified significant purchasing patterns, with the strongest valid rule being the association between Sweet Snacks and Ngmie (Support: 6.4%, Confidence: 80.0%, Lift Ratio: 1.102). The findings transition the use of FP-Growth from a routine application into a practical decision-support tool, providing the MSME management with a strategic basis for menu bundling, cross-selling opportunities, and targeted inventory planning. Only two of the three generated rules passed the Lift Ratio validation.

* Corresponding author: firman.noorhasan@uhamka.ac.id

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1. Introduction

The rapid growth of digitalization in Micro, Small, and Medium Enterprises (MSMEs) has led to a significant increase in sales transaction data generated daily [1]. However, most of these data are still utilized only as transaction records and have not been processed into valuable information to support business decision-making. Kedai Mie Rahma, a culinary MSME, faces challenges in determining promotional strategies, designing menu packages, and managing raw material inventories due to the lack of systematic analysis of customer purchasing patterns [2], [3].

Association rule mining is a well-established data mining technique used to identify correlations between items within large datasets [4], [5]. While the Apriori algorithm has been traditionally popular for this task [6], recent studies indicate that it faces scalability issues when handling growing datasets due to its candidate generation process, which requires multiple database scans [7]. In contrast, the FP-Growth (Frequent Pattern Growth) algorithm offers a more efficient approach by utilizing a compact FP-Tree structure, eliminating the need for candidate generation, and significantly reducing execution time and memory consumption [8], [9]. Despite the proven efficiency of FP-Growth, its application in the culinary MSME sector often stops at the identification of rules [10], without translating these mathematical associations into actionable, domain-specific business strategies [11]. Therefore, this study aims to address this specific gap. The primary research question guiding this study is: How can the FP-Growth algorithm be effectively utilized to extract valid association rules from raw transaction data to generate actionable cross-selling and menu bundling recommendations for a culinary MSME?

This research goes beyond merely applying a standard data mining pipeline to a new dataset. The novelty of this study lies in its focus on the direct operationalization of the algorithmic output. By calculating the Support, Confidence, and Lift Ratio of menu associations, this study transitions the FP-Growth method from a purely computational exercise into a practical decision-support framework. The findings are intended to provide MSME management with a data-driven basis for formulating bundle promotions, optimizing menu displays, and predicting inventory needs, thereby improving overall operational efficiency and sales performance.

2. Methods

The Knowledge Discovery in Databases architecture is used in the study to guarantee methodical, precise, and quantifiable data analysis [12]. The overall stages of the research are illustrated in Figure 1.

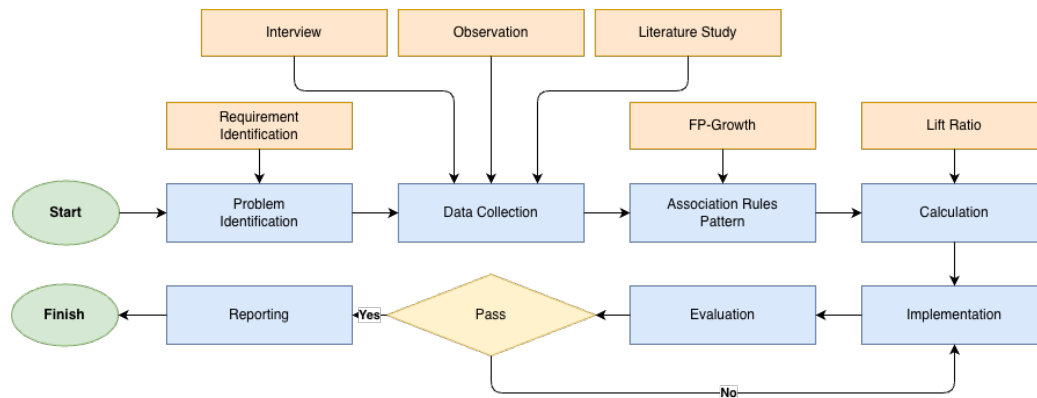


Figure 1. Research flowchart

2.1 Identification

This phase focuses on identifying the core business problems faced by Kedai Mie Rahma, in particular the difficulties in mapping out the menu items that are often preferred simultaneously by customers [13]. The identification of this problem serves as a basis for determining the limits of the data to be taken and establishing the parameters of association required by MSME management [14]. Furthermore, the identification of system needs is carried out to design an FP-Growth algorithm implementation scenario that is most aligned with operational conditions in the field [15].

2.2 Implementation

The implementation stage is the core of transaction data processing using data mining techniques, which are divided into several conditioning and analysis phases:

2.2.1 Data Selection

The study's data came from Kedai Mie Rahma's internal Point of Sale (POS) system [16]. The selection process involves filtering the table of historical monthly sales transactions to extract important variables, such as Transaction ID, Menu Item Name, and Date. Data that is considered irrelevant to the extraction of item combination patterns is discarded at this phase [17].

2.2.2 Data Preprocessing

Raw transaction data typically contains anomalies, such as double records, null values, or inconsistent record formats [18]. Pre-processing performs data cleansing tasks to prevent algorithms from misinterpreting customer shopping carts [19]. Clean data is an important prerequisite for producing highly accurate association rules [20].

2.2.3 Data Transformation

In this phase, the cleaned data is transformed into a tabular matrix format or itemset structure recognized by the data mining system [21]. The transaction format, which was originally a row-based entry, is grouped by Transaction ID to reflect one complete basket per customer purchase [22].

2.2.4 FP-Growth

The FP-Tree tree-based data structure is used in the implementation of the FP-Growth method to extract frequent itemsets [3]. This algorithm starts by reading the database to determine the Support value for every single item (1-Itemset). Whether a menu item appears frequently enough to be taken into account in the association rule is determined by this Support value. Equation (1) defines the computation for a single item of support.

$$\text{Support}(X) = \frac{\text{Number of Transactions Containing } X}{\text{Total Transactions}} \quad (1)$$

In contrast to the Apriori algorithm, the database scan in the FP-Growth method is only performed twice, resulting in a much shorter computation time [2]. This efficiency makes FP-Growth ideal for processing hundreds to thousands of lines of sales data within the scope of MSMEs [23].

2.2.5 Association Rule

Once the individual frequent itemsets are identified and filtered based on the minimum Support threshold, the system generates an association rule. To evaluate the relationships between different menu items, the system calculates Joint Support for a combination of products (2-Itemset or higher) and measures the conditional probability or reliability of those rules, known as Confidence. The Joint Support value for the product combination is determined using Equation (2), whereas the Confidence value of the rule is derived using Equation (3):

$$\text{Support}(X, Y) = \frac{\text{Number of Transactions Containing } X \cap Y}{\text{Total Transactions}} \quad (2)$$

$$\text{Confidence}(X \rightarrow Y) = \frac{\text{Number of Transactions Containing } X \cap Y}{\text{Number of Transactions Containing } X} \quad (3)$$

This metric assesses the conditional relationships between items [24]. Specifically, it shows how likely a customer is to purchase a secondary item (Consequent) if they have selected a primary item (Antecedent) [25].

2.2.6 Lift Ratio

To quantify the strength and validity of the produced association rules, the Lift Ratio calculation is employed as the final evaluation metric [26]. The Lift Ratio determines whether the association between items is really significant or just a random occurrence. The mathematical formula for calculating the Lift Ratio is defined in Equation (4):

$$\text{LiftRatio} = \frac{\text{Confidence}(X \rightarrow Y)}{\text{Support}(Y)} \quad (4)$$

Antecedent and consequent in the rule have a strong positive association if the resulting Lift value is greater than 1. Conversely, a score of less than 1 denotes a haphazard or weak association [27].

2.3 Evaluation

The final phase focuses on interpreting the rules of associations that have passed the Lift Ratio test to turn them into actionable business recommendations [28]. The results of the evaluation were analyzed to formulate strategic proposals related to item placement layout, menu package design (Bundling), and promotional discount programs centered on actual customer preferences [11]. It is anticipated that putting these suggestions into practice will immediately enhance Kedai Mie Rahma's future inventory control and sales performance.

3. Results and Discussion

3.1 Collection Data

The initial stage of finding association patterns began by collecting sales transaction datasets from the Point of Sales (POS) system of Kedai Mie Rahma. The historical data that was successfully collected amounted to 2,500 records of sales transactions that took place in the period from September 9, 2025 to December 9, 2025. The food and beverage menus sold in the period were grouped into several main variant clusters. The characteristics of the grouping of these menus are presented in detail in Table 1.

Table 1. Product Category

Category	Item
Ngemie	Ngemie Goreng LV.0–LV.5, Ngemie Soto LV.0–LV.5, Ngemie Kari LV.0–LV.5, Ngemie Rendang LV.0–LV.5
Salty Snacks	Cilor, French Fries, Mielor, Indomie Regular, Wonton Gravy, Shredded Chicken Cireng, Cireng Spicy Gravy, Soslor
Sweet Snacks	Baked Banana, Aromatic Cheese, Peach Lumer, Aroma Cheese + Topping, Banana Nugget
Jejeritan	Screaming Meatballs, Screaming Screams, Screaming Bones
Add Toppings	Substitute Eggs, Extra Spicy, Extra Kencur
Drinks	Teajuice, Sweet Tea, Tarik Tea, Pudding, Plain Tea, Nutrisari, Friday Sweet Tea, GoodDay Cappuccino
Seblak Package	Seblak 10K, Seblak12K, Seblak 14K, Seblak15K, Seblak17K, Save Couple, Fun
Seblak Buffet	Eggs, Meatballs, Small Sausages, Scissors, Bones, Brains, Batagor Tongue, Cikuwa

In order to make it easier for the system to perform data processing and computation on the FP-Growth algorithm, all menu items in Table 1 are initialized using unique alphanumeric coding. The process of naming these code labels ranges from codes A1, F1, to F2. The code representation scheme for each menu item is presented in Table 2.

Table 2. Product Coding

No.	Attribute Name	Attribute Code
1	Ngemie	A1
2	Salty Snacks	B1
3	Sweet Snacks	B2
4	Jejeritan	C1
5	Add Toppings	D1

6	Drinks	E1
7	Seblak Package	F1
8	Seblak Buffet	F2

After crossing the selection stage, the sales history data is cleaned of transaction record anomalies. Next, the data is converted into a format (market basket format) that groups the menu list based on a single line of consumer purchase memorandum. A sample representation of 2,500 transaction datasets that have been grouped and ready to be processed is visualized in Table 3.

Table 3. Sales Transaction Dataset

Transactions	Date	Itemset
1	9/7/2025	A1,E1,F2
2	9/7/2025	E1,F2
3	9/7/2025	E1,F2
4	9/7/2025	A1,F2
5	9/7/2025	B1,E1
6	9/7/2025	E1
7	9/7/2025	A1,E1,F2
8	9/7/2025	A1,E1,F2
...	...	...
2500	12/7/2025	E1,F2

The information from the shopping cart is then transformed into a binary tabulation through binomial processing. Items purchased in one transaction receipt will be given a value of 1, while menu items that are not selected by the consumer in the receipt are filled with a value of 0 until the 2,500th transaction is shown in Table 4.

Table 4. Binomial Processing

Transactions	A1	B1	B2	C1	D1	E1	F1	F2
1	1	0	0	0	0	1	0	1
2	0	0	0	0	0	1	0	1
3	0	0	0	0	0	1	0	1
4	1	0	0	0	0	0	0	1
5	0	1	0	0	0	1	0	0
6	0	0	0	0	0	1	0	0
7	1	0	0	0	0	1	0	1
8	1	0	0	0	0	1	0	1
9	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...
2500	0	0	0	0	0	1	0	1

3.2 FP-Growth Modelling

The primary input for the modeling of the Frequent Pattern Growth (FP-Growth) method is the binary dataset that has been organized in Table 4. Data processing is done by scanning the transaction database to convert the binary data stack into a dense frequency decision tree structure without eliminating the history of inter-Menu linkages.

This modeling process is carried out using RapidMiner software. The main operator of FP-Growth is connected to the create association rules by setting the minimum parameters of Support and minimum Confidence according to the needs of the research. The circuit flow of the algorithm modeling is presented in Figure 2.

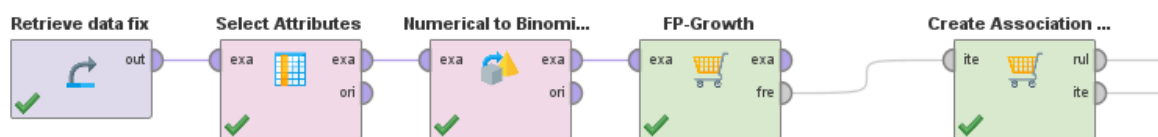


Figure 2. Modeling Design Using Rapid Miner

Through the modeling circuitry in Figure 2 above, RapidMiner scans transaction data to generate the most frequently occurring itemset combinations as well as strong final association rules.

3.2.1 Frequent Itemset

The search for frequent itemsets begins with calculating the pure number of frequencies from the occurrence of a single item (1-Itemset) to a combination of two items (2-Itemset). This frequency lookup is based on the accumulation of a binary value of 1 on each product code column from a total of 2,500 transactions. Equation (1) is used to determine the Support value for a single item, whereas Equation (2) is used to determine the Support value for a combination of two items. The resulting frequent itemsets are presented in Table 5.

Table 5. Frequency Itemset

Itemset	Quantity	Support
A1	1815	72.6%
E1	845	33.8%
A1,E1	605	24.2%
B2	200	8%
F2	192	7.7%
B1	180	7.2%
A1,B2	160	6.4%
A1,B1	132	5.3%

It can be seen that A1 (Ngemie) is the single item that dominates sales with a frequency of 1,815 transactions and the highest Support value of 72.6%. The second position was occupied by E1 (Beverages) with 845 transactions (33.8%). In addition to a single item, the table also shows a pattern of item combinations (2-Itemset) that are often purchased simultaneously by customers. The combination of A1 and E1 products (Ngemie and Beverages) became the combination of menus with the highest frequency, which was 605 transactions with a Support value of 24.2%. The set of frequent itemsets that have met the threshold requirements will then be processed to the stage of forming association rules.

3.2.2 Association Rule Generation

Building association rules is the next step after identifying the itemset common combinations in the preceding stage. This rule was developed using Equation (2) to determine the Support value for the itemset combination and Equation (3) to determine the degree of certainty. The Confidence parameter evaluates how likely a consumer is to buy a conclusion menu (Consequent) if they have ordered a particular premise menu (Antecedent). Rule combinations that don't reach the minimum trust percentage limit will be automatically ignored. The results of the association rule calculation from 2,500 transaction data are presented in Table 6.

Table 6. Results of the Formation of Association Rules

Rule	Support	Confidence
E1 => A1	605/2500 = 0.242 (24.2%)	605/845 = 0.716 (71.6%)
B1 => A1	132/2500 = 0.053 (5.3%)	132/180 = 0.733 (73.3%)
B2 => A1	160/2500 = 0.064 (6.4%)	160/200 = 0.800 (80.0%)

Therefore, it can be concluded that the rules that meet the requirements of Support and Confidence values, namely:

1. If consumers buy Drinks (E1), then consumers are also certain to buy Ngemie (A1), with a Support value of 24.2% and a Confidence level of 71.6%.
2. If consumers buy Salty Snacks (B1), then consumers tend to buy Ngemie (A1), with a Support value of 5.3% and a Confidence level of 73.3%.
3. If consumers buy Sweet Snacks (B2), then consumers tend to buy Ngemie (A1), with a Support value of 6.4% and a Confidence level of 80.0%.

3.3 Lift Ratio

The association rules that have been formed must be validated using the Lift Ratio calculation to ensure the relationships are not random coincidences. Using Equation (4) and the baseline probability of purchasing Ngemie (Support(A1) = $1815/2500 = 0.726$), the evaluation results are presented in Table 7.

Table 7. Testing Lift Ratio

No.	Rule	Support	Confidence	Lift Ratio
1	If Customer buy E1, then buy Ngemie A1	0.726	0.716	$0.716 / 0.726 = 0.986$
2	If Customer buy B1, then buy A1	0.726	0.733	$0.733 / 0.726 = 1.010$
3	If Customer buy B2, then buy Ngemie A1	0.726	0.800	$0.800 / 0.726 = 1.102$

Based on the Lift Ratio test, it can be concluded that rules 2 and 3 are valid because they yield a Lift Ratio > 1.0 , showing a positive correlation. This means customers buying Salty (B1) or Sweet Snacks (B2) are significantly more likely to purchase Ngemie (A1). In contrast, rule 1 ($E1 \Rightarrow A1$) has a Lift Ratio of $0.986 (< 1.0)$. This indicates that the purchase of Drinks (E1) has a slightly negative or independent association with A1, meaning they should not be explicitly bundled as a single dependent package.

3.4 Implementation of Association Rules

The rules of association have been validated by the value of the Lift Ratio, the management of Kedai Mie Rahma can implement the results into a real promotion strategy. Menu items that are proven to have a high engagement value, such as items A1, E1, and F2, are designed to be a single bundle offering. In addition, this pattern recommendation is implemented in the rearrangement of the menu image (layouting), by bringing the position of the main menu closer to the companion menu that is strongly associated to trigger additional purchasing decisions (Cross-selling). The translation of these validated rules into bundling and layout actions is summarised in Table 8.

Table 8. Implementation of Association Rules on Bundling Strategy and Menu Layout

No.	Rule	Menu Bundling	Menu Layouting
1	$B2 \Rightarrow A1$	Savory Sweet Package: The purchase of the Ngemie Menu gets a special price for the additional Sweet Snack Menu (Piscok Lumer/Aroma Cheese).	Placing the Sweet Snack Menu image on the main page of the Print menu list and the cashier's digital display right next to the Ngemie main menu.
2	$B1 \Rightarrow A1$	Paket Combo Kenyang: A special package that combines Ngemie's main menu with Salty Snacks (Cilor/Fries) as a side.	Arrange the order of the storefront of the companion menu (Salty Snacks) so that they are in the same row or directly after the Ngemie Menu category.

3.5 Evaluation of Business Impact

In the final evaluation stage, an in-depth review was conducted of the effectiveness of the results of the implementation of association rules from the FP-Growth algorithm on the operational performance of Kedai Mie Rahma MSMEs. The application of a menu packaging strategy (Bundling) based on the pattern of linkage between products has proven to be very relevant and effective in boosting the visibility of secondary items. Companion products (such as snacks or drinks) that were rarely purchased individually by consumers now have a high probability of selling because they are strategically juxtaposed with their main menu pairs (Cross-selling).

More than just a sales strategy, this valuable information (knowledge) extracted from the history of 2,500 customer transaction data provides transparency for store owners in the inventory management system. MSME owners can now estimate the procurement of raw material inventory needs more specifically, precisely, and data-driven. As a result, the efficiency of the shop supply chain becomes healthier so that the risk of operational losses due to lack of stock during high demand (stockout) and the accumulation of leftover foodstuffs that lead to spoilage (food waste) can be significantly minimized.

To provide a more systematic comparative picture of the direct impact of the application of the FP-Growth algorithm on business sustainability, a summary of the operational performance evaluation can be seen in Table 9.

Table 9. Comparison of Shop Operational Performance Before and After FP-Growth Implementation

No.	Operational Indicators	Current Status	Proposed Strategy Post FP-Growth Validation
1	Sales Strategy	Sales are focused on single items without a data-pattern-based packaging plan.	Implementation of targeted Bundling packages based on positively correlated rules ($B1 \Rightarrow A1$, $B2 \Rightarrow A1$).

2	Menu Layouting	Secondary item positioning is not optimized, leading to slow sales for snacks.	Layout rearrangement to trigger cross-selling by placing positively associated snacks closer to the main menu.
3	Procurement Management	Purchasing of kitchen raw materials is largely driven by instinct or rough estimates.	Stock prioritization can be specifically aligned with the historical frequency metrics of strong itemsets.

4. Conclusion

Based on the analysis of 2,500 sales transactions at Kedai Mie Rahma using the FP-Growth algorithm (minimum Support of 5% and minimum Confidence of 70%), this study has mapped consumer purchasing behaviors into association rules. However, the evaluation metric indicates that the algorithm's application yielded moderate rather than absolute results. Out of the three primary rules generated, only two demonstrated a valid positive correlation that exceeded the threshold: the association between Sweet Snacks and Ngemie (Lift Ratio = 1.102) and Salty Snacks and Ngemie (Lift Ratio = 1.010). Conversely, the association between Drinks and Ngemie failed the validation test (Lift Ratio = 0.986), indicating a random occurrence rather than a dependent relationship.

Instead of an immediate operational overhaul, these validated rules provide an initial, data-driven foundation for the MSME owner to design targeted cross-selling strategies, such as specific menu bundling (Ngemie with Sweet/Salty snacks) and optimized menu layout. By aligning stock procurement with these specific validated patterns, the MSME has a systematic basis that could potentially help estimate raw material needs and mitigate the risk of food waste or stockouts.

This study has several limitations. First, the scope is confined to a single culinary MSME with a relatively small dataset, limiting the generalizability of the findings to other culinary businesses. Second, the analysis relies solely on item frequencies and does not account for external variables such as seasonal trends, time of purchase, or promotional pricing.

For future research, it is highly recommended to implement these proposed bundling strategies in a real-world setting over a specific period to quantitatively measure the actual impact on sales volume and operational efficiency. Furthermore, future studies could integrate the FP-Growth algorithm directly into a real-time Point of Sales (POS) dashboard or compare its computational performance with other association algorithms, such as ECLAT or Apriori, using larger and more complex datasets.

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