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# Analysis of Product Purchase Patterns Using the Apriori Algorithm on FMCG Distributor Transaction Data in the Riau Region

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***Abstract*** *- This study investigates purchasing patterns of fast-moving consumer goods (FMCG) in Riau Province, Indonesia, using the Apriori algorithm within the Market Basket Analysis framework. Transaction data from a distributor comprising 4,422 transactions and 243 unique products across Pekanbaru, Kampar, and Rokan Hulu were analyzed to generate frequent itemsets and association rules, evaluated using support, confidence, and lift metrics. The application of a consistent minimum support and confidence threshold ensures statistically robust rule extraction across regions with different transaction scales.The results reveal strong intra-brand associations within the snack category, with several rules exhibiting lift values above ten, indicating systematic bundling behavior rather than random co-occurrence. These findings suggest that retailers tend to stock complementary product variants simultaneously, reflecting structured purchasing patterns at the outlet level. Regional comparison highlights differences in rule density across districts, shaped by transaction volume and the proportional effect of the support threshold, demonstrating how dataset scale influences association complexity. Overall, the study demonstrates that the Apriori algorithm effectively uncovers meaningful purchasing structures in distributor-level transaction data. The findings provide actionable insights for inventory management, regional distribution planning, and targeted promotions, while contributing to the literature by examining FMCG purchasing behavior in a multi-region distribution context using empirical distributor data.*

***Keywords***: *Apriori Algorithm; Association Rules; FMCG; Market Basket Analysis; Purchasing Patterns.*

## 1. INTRODUCTION

The development of information technology and the digitalization of retail distribution processes have generated massive volumes of sales transaction data (big transactional data), driving the need for purchase pattern analysis to support data-driven decision-making [1][2]. Such analysis not only aims to understand consumer behavior but also serves as a basis for designing more effective marketing strategies, including product bundling, product recommendations, shelf layout optimization and cross-selling strategies [3][4]. In the Fast-Moving Consumer Goods (FMCG) industry, which includes products with high turnover and relatively low cost such as packaged foods, beverages, personal care and household items, leveraging transaction data plays a strategic role in improving distribution efficiency, inventory management and overall competitiveness in an increasingly competitive market [5].

One commonly used approach to identify relationships among products in transactions is Market Basket Analysis (MBA), a data mining technique based on association rule mining that extracts patterns of item co-occurrence using statistical metrics such as support, confidence and lift [6][7]. Among various available algorithms, Apriori is the most widely used due to its simplicity, systematic identification of frequent itemsets and ease of interpreting results in the retail business context [8][9]. However, although the FP-Growth algorithm is known for its efficiency in handling large-scale datasets by eliminating candidate generation, this study employs the Apriori algorithm due to its simplicity and transparency in generating association rules. Compared to FP-Growth, Apriori provides a more interpretable and transparent rule generation process, which is more suitable for this study. Apriori allows a step-by-step evaluation of candidate itemsets, making the results easier to interpret and validate, especially for medium-sized retail transaction data. Additionally, the

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dataset used in this study is relatively manageable in size, so the computational limitations of Apriori do not significantly affect performance.

Both national and international studies have demonstrated the effectiveness of the Apriori algorithm in analyzing consumer purchase patterns across various retail contexts. Several studies indicate that association rules can support promotional strategies, product layout management and sales optimization [1][10]. Comparative research between Apriori and FP-Growth also shows that although FP-Growth is faster for large datasets, Apriori remains relevant for medium-sized datasets due to its more transparent and interpretable process [11][12]. MBA has also been implemented in web-based point-of-sale (POS) systems and e-commerce platforms to support automated product recommendations [13][14]. Most of these studies focus on a single store or region, without considering socio-economic variations across regions that may lead to different purchase patterns. Research in supermarkets and minimarkets within specific areas has revealed location-specific association patterns but lacks systematic multi-region comparative analysis [15][16]. Similarly, studies on electronics and computer stores are often limited to a single product category and geographic area [17][18], highlighting a research gap in retail distribution analysis across broader regional contexts.

In the FMCG distribution context in Riau Province, differences in regional characteristics, such as those in Pekanbaru, Kampar and Rokan Hulu, can influence variations in consumer purchase patterns due to differences in demographics, purchasing power and distribution access. Recent research confirms that region-based purchase pattern analysis contributes significantly to distribution planning, inventory optimization and the development of adaptive marketing strategies [19][20]. Therefore, the urgency of this study lies in the need for regional distributors and FMCG producers to understand product association patterns based on regional characteristics more comprehensively. Recent research confirms that association rule mining especially the Apriori algorithm remains widely applied in retail and e-commerce environments to reveal actionable purchasing insights, support cross-selling, and improve inventory and promotional strategies [21][22]. In addition, applying Apriori to transactional sales data has been shown to yield interpretable rule sets that support targeted marketing and operational decisions [23][24]. The dataset used in this study consists of 4,422 transaction records and 243 unique products (SKUs) collected from FMCG distributors across three regions in Riau Province, namely Pekanbaru, Kampar, and Rokan Hulu. Based on this background, this study aims to identify FMCG product purchase patterns using the Apriori algorithm on multi-region distribution data in Riau Province as a basis for formulating data-driven distribution and marketing strategies.

## 2. RESEARCH METHODOLOGY

This section describes the research methodology employed in this study, including the research design, data sources and characteristics, data preprocessing and transformation procedures, analytical techniques and multi-region comparative analysis. The methodology is structured systematically to ensure that the extracted patterns and association rules are valid, reliable and relevant for supporting distribution planning and marketing decision-making in multi-region FMCG networks. The overall research workflow is illustrated in Figure 1, which visually summarizes the sequential steps from research design to multi-region comparative analysis.

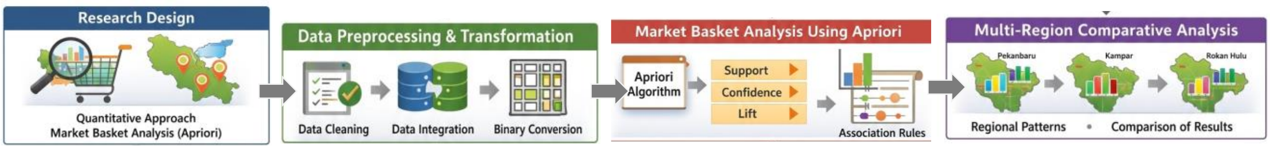


Figure 1. Research methodology.

### 2.1. Research Design

This study applies a quantitative approach using data mining techniques to analyze purchasing patterns of Fast Moving Consumer Goods (FMCG) products in multi-region distribution networks in Riau Province. The analytical method employed is Market Basket Analysis (MBA) using the Apriori algorithm to discover frequent itemsets and generate association rules between products. The Apriori algorithm was selected due to its high interpretability and systematic candidate generation mechanism, which remains relevant for medium-sized transaction datasets. The research follows the Knowledge Discovery in Databases (KDD) framework, encompassing data selection, preprocessing, transformation, data mining and interpretation stages to ensure extracted knowledge is valid and applicable for distribution planning and marketing strategies [25].

### 2.2. Data Source and Data Characteristics

The processed data consist of transactional sales records from FMCG distributors in three regions of Riau Province: Pekanbaru, Kampar and Rokan Hulu, including Transaction ID, transaction date, outlet identifier, product code, product name, product category, quantity purchased and region identifier. The unit of analysis is a single transaction representing a basket of products purchased simultaneously by an outlet or retailer, with the main variable being the presence or absence of specific FMCG products. The observation period covers several months to ensure pattern stability and sufficient transaction volume for association rule mining [26][27].

### 2.3. Data Preprocessing and Transformation

The preprocessing stage ensures data quality through initial cleaning by removing incomplete records, duplicate transaction IDs, and inconsistent product codes, while excluding transactions with missing essential attributes to prevent distortion in support calculations. Data integration then merges records from the three regions into a standardized format with unified product codes across regions. Data transformation converts the dataset into a binary transaction-item matrix, where rows represent transactions and columns represent unique FMCG products valued as 1 if present or 0 otherwise, which is required for Apriori computation. Items with extremely low frequency are filtered using a preliminary support threshold to enhance computational efficiency and reduce noise. Such preprocessing procedures are consistent with established data mining workflows, where data cleaning, integration, and transformation are critical steps prior to association rule mining [28]. Furthermore, support-based pruning is widely recommended to improve performance and scalability of Apriori-based analysis in retail transaction datasets [29][30]. To provide a clearer representation of the transformation process, examples of transaction data before and after transformation are presented in Table 1 and Table 2. Table 1 shows the original transaction format, where each transaction contains a list of purchased products based on transaction ID (NOFAKT). Based on the transaction data in Table 1, each transaction is converted into a binary representation as shown in Table 2.

Table 1. Excerpt of transaction data before transformation.

| NOFAKT | Products Purchased |
|---|---|
| 5123009652 | NN Fun Play Bubble Puff, GT Double Choco, Chitato Lite, Maxicorn, Chitato Sapi |
| 5123009653 | Chiki Balls, Chitato Lite, Qtela Balado |
| 5123009654 | Chitato Sapi, Chitato BBQ, Chiki Twist |

Table 2. Binary transaction-item matrix.

| NOFAKT | NN Fun Play | GT Double Choco | Chitato Lite | Maxicorn | Chitato Sapi | Chiki Balls | Qtela | Chitato BBQ | Chiki Twist |
|---|---|---|---|---|---|---|---|---|---|
| 5123009652 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 5123009653 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 5123009654 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 |

In this representation, a value of 1 indicates that the product is present in the transaction, while 0 indicates its absence. This transformation enables the Apriori algorithm to compute support values and identify frequent itemsets efficiently.

### 2.4. Market Basket Analysis Using Apriori Algorithm

Market Basket Analysis in this study was conducted using the Apriori algorithm to identify frequent itemsets (combinations of items that frequently appear together) based on a minimum support threshold and to generate association rules that satisfy a minimum confidence criterion. The Apriori algorithm operates based on the Apriori property, which states that all subsets of a frequent itemset must also be frequent. This principle helps reduce the number of candidate item combinations that need to be evaluated.

#### 2.4.1. Support

Support is used to measure how frequently an item or a combination of items appears within the entire set of transactions. Mathematically, support is formulated as follows:

$$\text{Support (A)} = \frac{\sigma \text{A}}{\text{N}} \tag{1}$$

$$\text{Support (A} \cup \text{B)} = \frac{\sigma(\text{A} \cup \text{B})}{N} \tag{2}$$

Where σ(A) is the number of transactions containing itemset A, σ(A∪B) is the number of transactions containing the combination of items A and B, and N is the total number of transactions. The support value indicates the frequency level of occurrence of an item or a combination of items within the dataset.

#### 2.4.2. Confidence

Confidence is used to measure the level of certainty or probability that item B will be purchased when item A is purchased. The confidence formula is expressed as follows:

$$\text{Confidence (A} \rightarrow \text{B)} = \frac{\text{Support (A} \rightarrow \text{B)}}{\text{Support (A)}} \tag{3}$$

A high confidence value indicates that the association rule has a strong level of reliability.

#### 2.4.3. Lift

Lift is used to measure the strength of the relationship between item A and item B compared to the likelihood of their co-occurrence occurring by random chance. The lift formula is expressed as follows:

$$\text{Lift (A} \rightarrow \text{B)} = \frac{\text{Confidence(A} \rightarrow \text{B)}}{\text{Support (B)}} \tag{4}$$

If the Lift value is greater than 1 (Lift > 1), it indicates a positive relationship between A and B, meaning that the two items occur together more frequently than would be expected by random chance.

#### 2.4.4. Parameter Determination

The minimum support and minimum confidence thresholds in this study were determined iteratively through several experimental trials to obtain a set of relevant association rules without generating an excessive number of rules (overfitting). Only association rules with a Lift value greater than 1 were retained for further analysis, as they indicate statistically and practically meaningful relationships from a business perspective.

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### 2.5. Multi-Region Comparative Analysis

The Apriori algorithm was applied separately to transaction datasets from Pekanbaru, Kampar and Rokan Hulu, followed by comparing frequent itemsets and association rules based on support, confidence and lift values to identify regional variations and common patterns. Result interpretation links significant rules to practical distribution strategies such as product bundling, regional inventory allocation and targeted promotions. Multi-region comparative analysis is crucial for understanding localized demand structures and enhancing supply chain responsiveness.

## 3. RESULTS AND DISCUSSION

### 3.1. Descriptive Analysis

The dataset analyzed in this study consists of 4,422 transactions and 243 unique Stock Keeping Units (SKUs) across three regions in Riau Province: Pekanbaru, Kampar and Rokan Hulu. A summary of the descriptive statistics is presented in Table 3**.** Transaction volumes vary considerably across regions, with Pekanbaru recording the highest number of transactions (3,243), followed by Kampar (917) and Rokan Hulu (262). The distribution of transactions across the three regions is presented in Table 4**.**

Table 3. Summary of descriptive statistics.

| Parameter | Value |
|---|---|
| Total Transactions | 4,422 |
| Unique Products (SKU) | 243 |
| Average Items per Transaction | 4.75 |

Table 4. Distribution of transactions by region.

| Region | Number of Transactions |
|---|---|
| Pekanbaru | 3,243 |
| Kampar | 917 |
| Rokan Hulu | 262 |

These differences highlight Pekanbaru's more intensive distribution activity, which is expected to yield more stable association patterns compared to the smaller datasets from Kampar and Rokan Hulu. On average, each transaction contains 4.75 products, indicating that outlets typically purchase multiple items simultaneously. This multi-product purchasing behavior strengthens the suitability of Market Basket Analysis, as the Apriori algorithm performs best with diverse item combinations. Overall, the dataset demonstrates sufficient volume and variety to support robust association rule mining, forming the basis for determining minimum support thresholds in subsequent analysis.

### 3.2. Frequent Itemset Analysis Using the Apriori Algorithm

The Apriori algorithm was applied to the filtered transaction dataset comprising 4,422 transactions from Pekanbaru, Kampar and Rokan Hulu. The transaction data were transformed into a binary matrix format, where each row represents a transaction and each column represents a product (SKU). A value of 1 indicates that the product appears in the transaction, while 0 indicates its absence. A minimum support threshold of 2% was applied, meaning that a product combination must appear in at least 2% of total transactions (approximately 88 transactions) to be considered frequent. This threshold ensures statistical relevance while maintaining sufficient rule generation for further analysis. The results show several dominant single-item and multi-item combinations. Table 5 presents the top frequent itemsets ranked by support value.

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Table 5. Top frequent itemsets based on support.

| No | Itemset | Support |
|---|---|---|
| 1 | Chitato BBQ 19.5gr Renceng | 0.2112 |
| 2 | Chitato Lite NOS 18.5 Renceng | 0.1893 |
| 3 | Chiki Twist Roasted Corn 22.5 | 0.1617 |
| 4 | Chitato Lite NOS 68gr | 0.1389 |
| 5 | Chitato BBQ 19.5gr Renceng, Chitato Lite NOS 18.5 Renceng | 0.1361 |
| 6 | Chitato Sapi Panggang 68 Gr | 0.1282 |
| 7 | Chitato Sapi Panggang 35 Gr | 0.1187 |
| 8 | Chitato BBQ 19.5gr Renceng, Chiki Twist Roasted Corn 22.5 | 0.0936 |
| 9 | Chitato Lite NOS 68gr, Chitato Sapi Panggang 68 Gr | 0.0816 |
| 10 | Chitato Lite NOS 18.5 Renceng, Chiki Twist Roasted Corn 22.5 | 0.0807 |

The results indicate that several snack products dominate transaction baskets, particularly variants of Chitato and Chiki Twist. The highest support value (21.12%) is observed for *Chitato BBQ 19.5gr Renceng*, meaning that this product appears in more than one-fifth of all transactions. This suggests strong market penetration and high consumer demand.

Multi-item combinations also show significant support values. For example, the combination of *Chitato BBQ 19.5gr Renceng* and *Chitato Lite NOS 18.5 Renceng* appears in 13.61% of transactions, indicating a strong co-purchasing pattern between these variants. Such patterns suggest complementary purchasing behavior and provide strategic insights for bundling and distribution planning. The dominance of similar product categories in frequent itemsets indicates that flavor or variant differentiation within the same brand plays a significant role in outlet purchasing decisions.

### 3.3. Association Rule Analysis

Following the identification of frequent itemsets, association rules were generated using a minimum confidence threshold of 60%. The resulting rules were evaluated using support, confidence and lift metrics to determine their statistical strength and practical relevance for distribution planning.

Table 6. Top association rules ranked by lift value.

| No | Antecedent | Consequent | Support | Confidence | Lift |
|---|---|---|---|---|---|
| 1 | Chitato Lite NOS 18.5 Renceng + Chitato Sapi Panggang | Chitato BBQ 19.5gr Renceng | 0.0237 | 0.6325 | **13.9157** |
| 2 | Chitato BBQ 120gr + Chitato Lite NOS 68gr | Chitato Lite NOS 120gr | 0.0203 | 0.6818 | **12.6151** |
| 3 | Chitato BBQ 120gr | Chitato Lite NOS 120gr | 0.0285 | 0.6058 | **11.2080** |
| 4 | Chitato BBQ 19.5gr Renceng + Maxicorn Roasted Corn | Chitato Lite NOS 18.5 Renceng | 0.0280 | 0.6108 | 7.5662 |
| 5 | Maxicorn Roasted Corn + Chiki Twist Roasted Corn | Chitato BBQ 19.5gr Renceng | 0.0280 | 0.6425 | 6.8625 |

The results as shown in Table 6 reveal several strong purchasing relationships. For example, if an outlet purchases Chitato BBQ 120gr, then there is a 60.58% probability that Chitato Lite NOS 120gr will also be purchased (lift = 11.21)**,** indicating that the joint occurrence of these products is more than eleven times higher than expected under independent conditions. Similarly, if Chitato Lite NOS 18.5 Renceng and Chitato Sapi Panggang are purchased together, then there is a 63.25% probability that Chitato BBQ 19.5gr Renceng will also be included in the same transaction (lift = 13.91), representing the strongest association identified in this study.

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The dominance of intra-brand associations suggests that outlets tend to stock multiple product variants simultaneously, reflecting brand-level bundling behavior rather than purely cross-brand complementarity. Overall, the consistently high lift and confidence values confirm robust inter-product relationships within the snack category and provide actionable insights for bundling strategies, coordinated distribution planning, and targeted cross-promotion initiatives.

### 3.4. Multi-Region Comparative Analysis

To examine regional differences in purchasing patterns, the Apriori algorithm was applied separately to transaction data from Pekanbaru, Kampar, and Rokan Hulu using a minimum support of 2% and a minimum confidence threshold of 60%. The results indicate substantial variation in the number of generated association rules across regions.

Table 7. Comparison of association rules across regions.

| Region | Number of Transactions | Number of Association Rules |
|---|---:|---:|
| Pekanbaru | 3,243 | 81 |
| Kampar | 917 | 651 |
| Rokan Hulu | 262 | 2,600 |

As shown in Table 7, Pekanbaru, despite having the largest transaction volume, produced the fewest association rules. In contrast, Rokan Hulu generated the highest number of rules even though it has the smallest number of transactions. This phenomenon can be explained by the proportional impact of the minimum support threshold. With a fixed support value of 2%, the absolute number of required co-occurrences differs significantly across regions. Smaller datasets require fewer transactions to meet the support threshold, leading to a larger number of detected rules.

These findings suggest that regional transaction scale influences the density of generated association rules. While dominant snack product combinations appear consistently across regions, smaller regions tend to exhibit more rule variations due to lower absolute support requirements. From a managerial perspective, this indicates that distribution strategies should consider regional transaction volume when interpreting association patterns, ensuring that high rule counts in smaller regions are evaluated cautiously in terms of statistical robustness.

## 4. CONCLUSIONS

This study analyzed product purchase patterns in the Riau region using the Apriori algorithm on FMCG distributor transaction data. The results indicate strong intra-brand associations among snack products, with several rules showing high lift values, meaning that certain product variants are frequently purchased together. These findings confirm consistent bundling behavior across retail outlets and demonstrate the effectiveness of association rule mining in identifying meaningful purchasing patterns. Regional comparison across Pekanbaru, Kampar, and Rokan Hulu reveals that transaction scale significantly influences the density of generated rules due to the proportional effect of the minimum support threshold. This suggests that purchasing pattern complexity varies by region and should be interpreted relative to dataset size. Overall, the findings provide practical insights for inventory management, regional distribution planning, and targeted promotional strategies in the FMCG sector.

However, this study has several limitations. The use of a fixed minimum support threshold across regions with different transaction volumes may affect the number of generated rules. In addition, the Apriori algorithm has relatively high computational complexity compared to FP-Growth, especially for larger datasets, and this study does not consider additional factors such as customer demographics or temporal patterns. Therefore, future research is recommended to apply adaptive threshold methods, incorporate additional variables, and explore alternative algorithms to improve analytical performance and scalability.

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